Visual Prompting: Modifying Pixel Space to Adapt Pre-trained Models

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Abstract

Prompting has recently become a popular paradigm for adapting language models to downstream tasks. Rather than fine-tuning model parameters or adding task-specific heads, this approach steers a model to perform a new task simply by adding a text prompt to the model’s inputs. In this paper, we explore the question: can we create prompts with pixels instead? In other words, can pre-trained vision models be adapted to a new task solely by adding pixels to their inputs? We introduce visual prompting, which learns a task-specific image perturbation such that a frozen pre-trained model prompted with this perturbation performs a new task. We discover that changing only a few pixels is enough to adapt models to new tasks and datasets, and performs on par with linear probing, the current de facto approach to lightweight adaptation. The surprising effectiveness of visual prompting provides a new perspective on how to adapt pre-trained models in vision, and opens up the possibility of adapting models solely through their inputs, which, unlike model parameters or outputs, are typically under an end-user’s control. Code is available at https://hjbahng.github.io/visual_prompting/.

1 Introduction

When we humans learn a new task, we tend to start from our current knowledge base and extrapolate thereof. A child who is starting to speak and comprehend sentences quickly develops the ability to parse the emotional context that accompanies a sentence. For example, the sentence "I missed the school bus" carries a particular emotion such that if followed by “I felt so [MASK]”, the child can provide an appropriate emotion word. This paradigm, aptly named prompting, has recently been popularized in NLP, where large pre-trained language models are adapted to new tasks by converting the downstream dataset into the format of the pre-training task. Without updating any of its parameters, the language model uses its existing knowledge base to fill in the mask in the provided prompt, hence becoming an expert in the new task. Currently, prompting methods are dominantly NLP-specific [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13], despite the fact that the framework serves a general purpose: adapt a pre-trained model by modifying the data space. In this paper, our goal is to develop a prompting method in the visual domain.

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Figure 1: **All you need is a single patch.** Given a frozen, pre-trained model (CLIP [1] in this example), we wish to adapt the model to perform well on a new downstream task. Adding a single, input-agnostic prompt to input images improves performance across all object categories in a dataset.

Inspired by the success in NLP, we propose a new paradigm for adapting pre-trained vision models called **visual prompting**, where we create prompts in the form of pixels. Broadly, we explore the question: *can we steer visual models to solve a new task by only modifying the pixel space?* We learn a task-specific image perturbation, such that a frozen model prompted with this perturbation can perform a new task. While, at a glance, visual prompts look like adversarial examples (Figure 1), they enable a pre-trained model to increase performance on a task. By solely modifying the per-task prompt, we can steer the pre-trained model to perform different tasks (Figure 3).

How is visual prompting different from existing adaptation methods? Currently in vision, standard adaptation methods are fine-tuning and linear probing. Both approaches require some level of access to the model: entire parameters in the case of fine-tuning and model outputs (usually activations at the penultimate layer) in the case of linear probes. In contrast, visual prompting adapts the input to a model. After acquiring the visual prompt, it does not require model access at test time. This opens up unique applications; input-space adaptation puts control in the hands of the end-user of the system. For instance, a pedestrian could wear a visual prompt that improves their visibility to cars, without having access to the car itself, nor its vision system.

We apply our method to a wide range of pre-trained models and datasets. We discover that visual prompting is effective at adapting pre-trained models to new tasks and domains, sometimes surpassing the performance of a linear probe. While CLIP, a vision-language model, focuses on using text prompts for zero-shot transfer, we show that visual prompts can substantially boost performance while compensating for low-quality text prompts. Furthermore, we show that visual prompts can be more generally applied to arbitrary vision models, without any modification to the pre-trained parameters and architecture. By applying a visual prompt to input images, the frozen model is able to learn a mapping to unseen classes.

Note that our goal is not to achieve the state-of-the-art performance on specific tasks, but instead to broadly explore a new paradigm for visual adaptation. Our primary research question is: does prompting work in *pixel space*? In particular, how far can we improve adaptation to a new task *solely by modifying pixels*? Our primary contribution is to demonstrate that visual prompting produces reasonable results on a wide variety of visual models and datasets. Our second contribution is to present a simple approach.
– a single, input-agnostic prompt – is sufficient to achieve promising results, and to analyze the effects of several important factors for good performance. The surprising effectiveness of visual prompting provides a new perspective on how to adapt and use pre-trained models in vision.

2 Related Work

2.1 Natural Language Prompting

Visual prompting is inspired by the recent success in natural language prompting. Prompting in NLP reformulates the downstream dataset into a (masked) language modeling problem, so that a frozen language model directly adapts to a new task. A prompt consists of constructing a task-specific template (e.g. “I felt so [MASK]”) and label words (e.g. “happy/horrible”) to fill in the blank [7]. However, manually designing the right prompt requires domain expertise and significant amount of effort.

Prefix tuning [8] or prompt tuning [13] mitigates this problem by directly optimizing continuous prompts while having the model parameters fixed. Prefix tuning learns a task-specific continuous vector (i.e. prefix) that allows language models to adapt to various natural language generation tasks. Prompt tuning optimizes the prompt by maximizing the likelihood of $Y \mid X$ through backpropagation. When applied to large models with billions of parameters, a properly optimized prompt achieves competitive performance to fine-tuning the entire model, while significantly reducing memory usage and per-task storage. As prompt in pixel space is inherently continuous, we follow this line of work and optimize the pixels directly.
2.2 Prompting with Images

There have been initial approaches that attempt to prompt with images. Similar to prefix tuning, Frozen [14] creates a image-conditional prompt by training a vision encoder using gradients from a frozen language model. The images are represented as a continuous embedding from the vision encoder and used as a visual prefix to allow frozen language models to perform multi-modal tasks. CPT [15] converts visual grounding into a fill-in-the-blank problem by creating visual prompts with colored blocks and color-based textual prompts. However, both of these approaches focus on extending the capabilities of a language-based model. On the other hand, visual prompting primarily focuses on applying prompting to visual representations and datasets. In other words, we assume that pre-trained models consist of a visual encoder and focus on reformulating image datasets.

2.3 Adapting Pre-trained Models

Figure 2 provides a summary of different methods for adapting a pre-trained model. Fine-tuning and linear probes are highly flexible in their usage: they can be used to adapt the model to a new domain of inputs or to a new task with different output semantics. However, they also require some level of access to the model: parameters in the case of fine-tuning and model outputs (usually activations at the penultimate layer) in the case of linear probes. Domain adaptation is an interesting alternative to model adaptation in that it only modifies the inputs to the model using techniques such as image-to-image translation [16, 17]. Like domain adaptation, visual prompting also modifies the inputs to a model. Therefore, once the end user has found the visual prompt, it does not require having control over the model itself at test time. This opens up unique applications; for example, users can feed domain-adapted images to online APIs that can only be manipulated via their inputs. Domain adaptation focuses on adapting a source domain to look like a target domain, requiring both source and target datasets available at hand. On the other hand, we demonstrate that visual prompting can steer model in more arbitrary ways; for example, a model that performs one classification task can be adapted to perform an entirely different classification task, with new output semantics, just by perturbing the input pixels. Also, whereas domain adaptation methods are typically input-conditional, the visual prompts we explore in this paper are fixed (i.e. input-agnostic) across an entire dataset, as in NLP where the same natural language prompt is added to all model queries.

2.4 Adversarial and Unadversarial Examples

There are prior works on introducing perturbation in the pixel space to change the prediction of a deep model. If the perturbations are designed to confuse the model, they are considered adversarial examples [18]. In contrast, unadversarial examples aim to improve the model’s performance [?]. While these works have a commonality with our work in that they introduce perturbations in pixel space, our method learn a single perturbation per dataset (i.e. class-agnostic). In other words, we don’t need a priori knowledge about the model’s pre-trained classes. Moreover, our perturbations are quite simple and non-invasive to the images. This is important in applications where image distortion is prohibitive, e.g. when human observation is required or when other information acquisition from the image is needed.
(a) Adding a single visual prompt to every image increases performance on a task.

(b) Given an image, changing the visual prompt causes the model to perform different tasks.

Figure 3: How visual prompting works. Given a frozen pre-trained model, (a) it improves performance on a task, or (b) enables the model to perform different tasks. Note that the prompts and numbers are actual results using Instagram-pretrained ResNeXt [19].

3 Visual Prompting Method

3.1 Intuition

Prompting is an approach that changes model behavior by reformulating the dataset, while leaving the model parameters fixed. Essentially, prompts provide task-specific context (e.g. "TL;DR: " for text summarization) and reduce the distribution gap between the pre-trained data and downstream data, enabling better transfer. Likewise, we explore the idea of creating prompts in pixel space that steer a vision model to perform a new task without updating its parameters. However, as pixel space is less discrete compared to natural language, it is difficult to hand-craft prompts as in NLP (e.g. "a photo of a [LABEL]" for image classification). In fact, it is unclear what type of visual context is useful for each downstream task (e.g. what visual information would be useful for classifying satellite images?). Therefore, we use a simple gradient-based approach where we directly optimize the visual prompt.
3.2 Formulation

Our goal is to adapt pre-trained models to downstream tasks by only modifying the pixels of the input images. We present a simple approach where we learn a single, fixed prompt per task. Given a frozen pre-trained model \( F \) and a downstream task dataset \( D = \{(x_1, y_1), \ldots, (x_m, y_m)\} \), our objective is to learn a visual prompt \( v_\phi \) parameterized by \( \phi \). The prompt is added to the input image to form a prompted image \( x + v_\phi \). During training, the model maximizes the likelihood of the correct label \( y \),

\[
\max_{\phi} P_{\theta,\phi}(y|x + v_\phi),
\]

while the gradient updates are applied only to the prompt parameters \( \phi \) and the model parameters \( \theta \) remain frozen. During evaluation, we apply the optimized prompt to all test images,

\[
X_{\text{test}} = \{x_1 + v_\phi, \ldots, x_n + v_\phi\},
\]

which are then processed through the frozen model \( F \). Note that we optimize a single input-agnostic prompt, while linear probes operate over input-conditional activations.

3.3 Pre-trained Models

Prompting in pixel form can essentially be applied to any visual representation. Therefore, we apply visual prompting to one vision-language model and three standard vision models: CLIP [1], Instagram-pretrained ResNeXt (Instagram) [19], Big Transfer (BiT-M) [20], and ResNet trained on ImageNet-1k (RN50) [21, 22]. CLIP is a vision-language model that is able to perform zero-shot transfer to unseen classes using text prompts. In contrast, vision models are typically trained to predict a fixed set of predetermined classes and require learning a separate layer to predict unseen classes. In this work, we mainly explore two questions: How much does visual prompting help to improve performance of a text-prompted CLIP? Furthermore, can visual prompts be generally used to adapt arbitrary vision models? Despite the restricted generality of standard vision models, we experiment how far can we change the mapping from the pre-trained task (e.g. ImageNet-1k) to a new task (e.g. satellite image classification) solely by modifying the pixel space; we do not introduce additional layers to the model. We summarize the pre-trained model details in the Appendix 5. We select models across varying input modalities, pre-trained dataset sizes, and model architectures to evaluate the generalizability of our method. For Instagram-pretrained ResNeXt, we use the model additionally fine-tuned on ImageNet-1k.

3.4 Prompt Design

There are several ways to design a visual prompt in terms of template and size. We explore three visual templates: pixel patch at random location, pixel patch at fixed location, and padding. We explore various prompt sizes \( p \), where the actual number of parameters is \( C \times p^2 \) for patches and \( 2Cp(H-p) + 2Cp(W-p) \) for padding, where \( C, H, W \) are the image channels, height and width respectively. Section 6.2 shows that padding with \( p = 30 \) achieves the best performance over other design choices. We use this as default for all our experiments.

3.5 Mapping to Unseen Classes

Our goal is to adapt a frozen pre-trained model without any modification to its architecture and pre-trained weights, i.e. we restrict our learning to pixel space. To establish a mapping to a new set of classes, we take a different approach for vision models and CLIP. Standard vision models treat image
classes as a numeric id (e.g. “cat” is mapped to “index 1”). Thus, we arbitrarily map downstream class indices to pre-trained class indices, and discard unassigned indices for loss computation. For CLIP, a vision-language model, we follow the original approach of using text prompts for image classification, where class names are prompted by context-bearing words (e.g. “a photo of a [ cat ]”) for zero-shot transfer.

3.6 Implementation Details

For CLIP, the objective function is identical to its evaluation setting, i.e. we only compute cross entropy loss over images, where a set of prompted text strings is processed through the text encoder to produce weights of a linear classifier [1]. For vision models, we compute cross entropy loss over new class indices. For all experiments, we use the padding template with prompt size of 30. All images are resized to $224 \times 224$ to match the input size of pre-trained models. All visual prompts are trained for 1,000 epochs. We use SGD with a learning rate of 40, which is decayed using cosine schedule [23]. We use a batch size of 256 for CLIP, 128 for BiT-M and RN50, and 32 for Instagram. For linear probing, we follow the default setting in the original paper [1]; we discard the text encoder and learn a linear layer on top of the frozen image encoder.

4 Experimental Setup

4.1 Datasets

To evaluate how our method adapts to new tasks and domains, we select 15 datasets that measure in-distribution and out-of-distribution performance. We learn the visual prompt on the training set and evaluate its performance on test sets (i.i.d. or o.o.d.). For in-distribution performance, we evaluate across 12 datasets: CIFAR100, CIFAR10 [24], Flowers102 [25], Food101 [26], EuroSAT [27], SUN397 [28], DTD [29], UCF101 [30], SVHN [31], OxfordPets [32], Resisc45 [33], and CLEVR [34]. For out-of-distribution performance, i.e. training distribution differs from the test distribution, we evaluate on three image classification datasets in WILDS [35]: Camelyon17 [36], FMoW [37], and iWildCAM [38]. For Camelyon17, training and test sets comprise tissue patches from different hospitals. For FMoW, training and test sets are from different regions and years. Finally, iWildCAM consists of photos from disjoint sets of camera traps.

4.2 Baseline Methods

We compare visual prompting with text prompting (i.e. “zero-shot” CLIP) and linear probing. For text-prompted CLIP, we use the prompt “This is a photo of a [ LABEL ]” as default. For CLEVR, we use “This is a photo of [ LABEL ] objects”, with class label “three” to “ten”. For Camelyon17, we use “a tissue region [ LABEL ] tumor”, with class label “containing” and “not containing”. While CLIP can perform zero-shot transfer with text prompting, traditional vision (i.e. uni-modal) models are not equipped with this flexibility. Thus, we report the random accuracy where pre-trained class indices are arbitrarily mapped to class indices of a new task, with no parameter update. Note that visual prompting is restricted to learning in pixel space, thus it may be used with linear probing or fine-tuning for better performance.
Table 1: In-distribution test accuracy across 12 datasets using CLIP. TP, VP, LP, and FT refer to text prompt, visual prompt, linear probing, and fine-tuning respectively. Using visual prompts allows 24% performance gain compared to using text prompts only.

| Model | Adaptation | CIFAR100 | CIFAR10 | Flowers | Food | EuroSAT | SUN | UCF | SVHN | Pets | DTD | RESISC | CLEVR | Average |
|-------|------------|---------|---------|---------|------|---------|-----|-----|------|------|-----|--------|-------|---------|
| CLIP  | TP         | 63.1    | 89.0    | 61.9    | 79.8 | 40.0    | 60.0| 59.9| 5.1  | 85.9 | 43.0| 42.4   | 20.2  | 54.2    |
| CLIP  | TP + VP    | 75.3    | 94.2    | 70.3    | 78.9 | **96.4**| 60.6| 66.1| 88.4 | 85.0 | 57.1| 84.5   | **81.4**| 78.2    |
| CLIP  | LP         | 80.0    | 95.0    | **96.9**| 95.3 | 75.0    | **83.3**| 65.4| 89.2 | **74.6**| 92.3| 66.0   | 83.1  |         |
| CLIP  | FT         | **82.1**| **95.8**| **97.4**| 80.5 | 97.9    | 80.9| 95.7| 88.5 | 72.3 | **93.3**| **94.4**| **86.9**|

Figure 4: How visual prompting improves text-prompted CLIP performance. The bars indicate the gain (or loss) in accuracy obtained by adding a single visual prompt to all the images in each dataset (one fixed prompt per dataset).

5 Main Results

Table 1 shows average in-distribution test accuracy across 12 datasets for CLIP. Visual prompting achieves 24% performance gain compared to using text prompt only (i.e. "zero-shot transfer" in the original paper). In particular, visual prompting – with the simplest approach of adding a single, fixed prompt – achieves outperforms linear probing on EuroSAT, SVHN, and CLEVR, by 1.1%, 23%, and 15.4% respectively.

On the other hand, traditional vision pre-trained models are fixed to a predetermined set of classes and usually require introducing a separate task-specific head to adapt to new tasks. In our experiments, we measure how far visual prompting can change the mapping from the pre-trained task (e.g. ImageNet-1k) to a new task (e.g. satellite image classification) solely by modifying the input space, with zero modification to the model. To our surprise, Table 2 shows that visual prompting achieves promising results across diverse vision pre-trained models, sometimes surpassing the performance of linear probing (e.g. SVHN and CLEVR).
Table 2: In-distribution test accuracy across 12 datasets using vision pre-trained models. VP and LP refer to visual prompt and linear probe respectively.

| Model     | Adaptation | CIFAR100 | CIFAR10 | Flowers | Food | EuroSAT | SUN | UCF | SVHN | Pets | DTD | RESISC | CLEVR | Average |
|-----------|------------|---------|---------|---------|------|---------|-----|-----|------|------|-----|--------|-------|---------|
| Instagram | -          | 1.5     | 7.0     | 1.5     | 0.8  | 7.2     | 0.3 | 0.5 | 12.7 | 1.2  | 2.1 | 2.4    | 15.4  | 4.4     |
| Instagram | VP         | 16.7    | 62.1    | 22.9    | 9.9  | 85.4    | 2.2 | 15.4| 53.8 | 18.6 | 29.1| 41.4   | 30.9  | 32.4    |
| Instagram | LP         | **64.0**| **90.1**| **92.7**| **65.8**| **90.6**| **58.1**| **76.6**| **48.0**| **94.5**| **70.9**| **79.2**| **30.2**| **71.7**|
| BiT-M     | -          | 0.7     | 9.6     | 0.4     | 0.7  | 16.0    | 0.2 | 0.9 | 6.1  | 4.2  | 2.6 | 3.2    | 13.3  | 4.8     |
| BiT-M     | VP         | 16.2    | 53.6    | 29.2    | 11.6 | 72.5    | 2.6 | 16.6| 56.3 | 24.7 | 30.0| 43.0   | 34.8  | 32.6    |
| BiT-M     | LP         | **73.0**| **90.8**| **99.1**| **72.6**| **94.4**| **49.5**| **72.9**| **49.8**| **85.2**| **68.4**| **87.7**| **28.4**| **72.6**|
| RN50      | -          | 1.5     | 10.0    | 1.6     | 0.8  | 7.7     | 0.3 | 1.3 | 21.6 | 0.9  | 2.2 | 4.6    | 11.7  | 5.3     |
| RN50      | VP         | 10.1    | 54.5    | 14.0    | 5.1  | 78.7    | 1.1 | 9.5 | 57.1 | 10.8 | 8.2 | 29.9   | 29.5  | 25.7    |
| RN50      | LP         | **67.7**| **87.7**| **92.7**| **62.5**| **94.5**| **57.5**| **69.4**| **60.3**| **91.1**| **66.7**| **87.1**| **32.6**| **72.5**|

5.1 Robustness to Distribution Shift

Table 3 and Table 4 show that visual prompting is robust to distribution shift. Using the WILDS benchmark [35], we learn visual prompts from training sets that contain images from a particular domain, and see how it transfers to test sets from different domains (e.g. images from different hospitals, regions, years, cameras). Compared to in-distribution results, we observe a general boost in accuracy gain across all pre-trained models, and the performance gap with linear probing is further reduced. In particular, for Instagram-pretrained ResNeXt (Instagram), visual prompting outperforms linear probing on Camelyon17 by 9.7%.

Table 3: Out-of-distribution test accuracy on WILDS using CLIP. TP, VP, and LP refer to text prompt, visual prompt, and linear probe respectively.

| Model     | Method | iWILDCAM | FMoW | Camelyon17 | Average |
|-----------|--------|----------|------|------------|---------|
| CLIP      | TP     | 14.1     | 13.5 | 52.7       | 26.8    |
| CLIP      | TP + VP| 51.7     | 32.9 | **89.8**   | 58.1    |
| CLIP      | LP     | **66.7** | **36.3** | 84.9 | **62.6** |

Table 4: Out-of-distribution test accuracy on WILDS using vision pre-trained models. TP, VP, and LP refer to text prompt, visual prompt, and linear probe respectively.

| Model     | Method | iWILDCAM | FMoW | Camelyon17 | Average |
|-----------|--------|----------|------|------------|---------|
| Instagram | -      | 0.1      | 1.6  | 49.9       | 17.2    |
| Instagram | VP     | 52.2     | 14.0 | **87.1**   | 51.1    |
| Instagram | LP     | **64.1** | **22.7** | 77.4 | **54.7** |
| BiT-M     | -      | 0.0      | 1.6  | 50.0       | 17.2    |
| BiT-M     | VP     | 48.7     | 15.7 | 83.3       | 49.2    |
| BiT-M     | LP     | **55.9** | **22.3** | **89.0** | **55.7** |
| RN50      | -      | 0.3      | 1.6  | 55.4       | 19.1    |
| RN50      | VP     | 51.9     | 12.6 | 84.5       | 49.7    |
| RN50      | LP     | **62.7** | **28.7** | **90.2** | **60.5** |
5.2 How Do Text Prompts Affect Learning a Visual Prompt?

When using CLIP, a vision-language model, our learning signal is dependent on the text prompt we use. It has been reported that CLIP’s zero-shot accuracy can be significantly improved by using a better text prompt [1]. Therefore, we hypothesize that the quality of text prompt affects the performance of visual prompts. We measure the quality of text prompt by the zero-shot performance of CLIP and measure performance on EuroSAT. Figure 5 shows that the performance gain from visual prompting is higher for text prompts with low zero-shot performance. This highlights the usefulness of visual prompts. While manually searching for the best text prompt is extremely laborious, visual prompting can compensate for low-quality text prompts.

![Figure 5: Visual prompts compensate for low-quality text prompts.](image)

6 What Properties Make for a Good Visual Prompt?

The main results show that prompting in pixel space varies substantially for different datasets. This naturally brings up the question: what properties make for a good visual prompt? We evaluate this in terms of distribution gap from the pre-trained dataset and perceptual diversity (Section 6.1) and prompt design (Section 6.2).

6.1 Distribution Gap and Dataset Diversity

We observe that the performance of visual prompting varies across different datasets. While the best-performing datasets achieve up to a 83.2% accuracy gain over zero shot, the worst-performing datasets achieve less than 1% gain in accuracy. To explain this phenomenon, we first hypothesize that visual prompts bridge the distribution gap by converting the unfamiliar downstream dataset to look more similar to the pre-trained dataset. Under this hypothesis, visual prompting would not help datasets already within the pre-trained distribution, yet could significantly help datasets that are severely out-of-distribution. Another hypothesis is that a single visual prompt may fail to capture the full diversity of a dataset. For all experiments, we learn a single prompt per dataset. While this may be sufficient for datasets with low perceptual diversity, it may fail to capture the full distribution as the diversity increases. We validate this hypothesis by measuring the distributional similarity between ImageNet and
Figure 6: What properties of the downstream dataset affect performance? We see a general performance gain as (1) datasets become more out-of-distribution to ImageNet, and (2) perceptual diversity of a dataset decreases.

Figure 7: How does prompt design affect performance? Effect of different prompt template and size on visual prompting performance.

downstream datasets using the FID score [39]. We compare these scores to the accuracy gain from visual prompting. Due to computation limitations, we randomly sample 100k images from the ImageNet-1k training set to compute these metrics. Furthermore, we measure perceptual diversity using LPIPS [40]. For each dataset, we measure LPIPS between two randomly sampled image pairs and report the average score. Figure 6 shows that visual prompting performs well as the downstream dataset becomes severely out-of-distribution, and the performance decreases as perceptual diversity increases.

6.2 Prompt Design

Choosing the right template and size of prompt can highly affect performance. We perform an ablation study on three different templates: pixel patch at random location, pixel patch at fixed location, and padding, across prompt size $p = 1, \ldots, 224$. We measure accuracy on the EuroSAT dataset using a frozen, pre-trained CLIP. Figure 7 shows that using a fixed-location template (i.e. padding, fixed patch) yields better performance. For fixed-location templates, we find that performance improves as prompt size increases (i.e. more trainable parameters), then it starts to drop for +70k parameters. Furthermore, we surprisingly find that our simplest approach – solely adding a single-pixel prompt – can yield a 3% improvement over text-prompted CLIP (Figure 8). Refer to Section 6.2 on how the actual number of parameters are calculated.
7 Discussion

In this paper, we have presented a method to perturb inputs to a pretrained model in a manner which improves classification accuracy. A broader interpretation of visual prompting is to think of it as a way to steer a pre-trained model in any direction by modifying its input space. For instance, a visual prompt for an image-to-image model could be used to change the visual style of the input. Even though we have explored “universal” visual prompts in this work (i.e. fixed prompts that apply to any input image), prompts could also be made input-conditional and hence less universal but perhaps more accurate. The specific design choices including (a) input-specific or input-agnostic, (b) improving or decreasing accuracy, and (c) type of the pretrained-model, can be modified to create future interesting applications of prompting.

One natural question that arises following our exposition is in what situations would one prefer visual prompting over finetuning or a linear probe? Finetuning assumes that the model can be modified which may not always be the case (e.g. if the model is exposed by a API owned by a third-party). While prompting does under-perform linear probe in some cases, we would like to stress that the goal of this work is to show the existence of a prompting mechanism in “pixel space”, which works across multiple datasets and pretrained models, and reveals new avenues for how vision models can be effectively adapted. Our focus in this work is not to outperform state-of-the-art performance; we note that there are several approaches one could use to improve performance further including ensembling multiple prompts, using prompts in conjunction with linear probes or fine-tuning, or scaling of the pre-trained model (e.g. ViT-L/14 of CLIP, which is unfortunately not available to the public). We leave these for future work.

8 Conclusion

While standard adaptation methods in vision focus on introducing a separate task-specific head and adapt the model parameters or activations, we introduce the concept of adapting pre-trained models by only modifying the input space. We use a gradient-based scheme to learn a single, input-agnostic perturbation (i.e. visual prompt) that can be used to improve performance on a task; changing the visual prompt enables the model to perform different tasks. Through various experiments across pre-trained models of different architectures and modalities, we have demonstrated that prompting in pixel space indeed works successfully. We hope that our unique findings will spur further research into: 1) better understanding pixel space perturbations, and why they are so effective at steering deep networks, and 2) developing better visual prompts that further add to our repertoire of mechanisms for creating flexible and adaptable vision systems.

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Appendix

Table 5: Overview of pre-trained models.

| Model | Architecture | Modality | Pre-trained Dataset | Objective       |
|-------|--------------|----------|---------------------|-----------------|
| CLIP  | ViT-B/32     | Vision-language | 400M image-text pairs | Contrastive     |
| Instagram [19] | ResNet101-32x8d | Vision | 3.5B Instagram photos | Cross Entropy   |
| BiT-M [20] | ResNet-50 | Vision | 14M ImageNet-21k | Cross Entropy   |
| RN50 [21] | ResNet-50 | Vision | 1.2M ImageNet-1k | Cross Entropy   |

8.1 Dataset Statistics

Table 6: Description of the datasets and the corresponding text prompt used for CLIP.

| Dataset        | Train Size | Validation Size | Test Size | Classes | Text Prompt                          |
|----------------|------------|-----------------|-----------|---------|--------------------------------------|
| CIFAR100       | 50,000     | -               | 10,000    | 100     | “This is a photo of a {}”             |
| CIFAR10        | 50,000     | -               | 10,000    | 10      | “This is a photo of a {}”             |
| Flowers102     | 4,093      | 1,633           | 2,463     | 102     | “This is a photo of a {}”             |
| Food101        | 50,500     | 20,200          | 30,300    | 101     | “This is a photo of a {}”             |
| EuroSAT        | 13,500     | 5,400           | 8,100     | 10      | “This is a photo of a {}”             |
| SUN397         | 15,888     | 3,970           | 19,850    | 397     | “This is a photo of a {}”             |
| UCF101         | 7,639      | 1,898           | 3,783     | 101     | “This is a photo of a {}”             |
| SVHN           | 73,257     | -               | 26,032    | 10      | “This is a photo of a {}”             |
| OxfordPets     | 2,944      | 736             | 3,669     | 37      | “This is a photo of a {}”             |
| DTD            | 2,820      | 1,128           | 1,692     | 47      | “This is a photo of a {}”             |
| Resisc45       | 18,900     | 6,300           | 6,300     | 45      | “This is a photo of a {}”             |
| CLEVR/Count    | 70,000     | -               | 15,000    | 8       | “This is a photo of {} objects”      |
| iWildCAM       | 129,809    | 14,961          | 42,791    | 182     | “This is a photo of a {}”             |
| FMoW           | 76,863     | 19,915          | 22,108    | 62      | “This is a photo of a {}”             |
| Camelyon17     | 302,436    | 34,904          | 85,054    | 2       | “a tissue region {} tumor”           |

Figure 9: Average few-shot results across 12 datasets. Note that text prompt (TP) doesn’t require training (i.e. zero shot).
8.2 Few-shot Results

We measure the performance of visual prompting under few-shot settings. For few-shot experiments, we only measure accuracy on 12 in-distribution datasets. The models are trained \(N\)-shots for \(N \in \{1, 2, 4, 8, 16\}\) and evaluated on the entire test set. In Figure 9, we visualize the average performance of visual prompting and linear probe across 12 datasets using CLIP as the base model. While few-shot linear probe suffers overfitting and often falls below zero-shot accuracy, visual prompting shows robust performance across different training set size.

8.3 Visualizing Prompts

In Figure 10, we visualize the prompts for different datasets and pre-trained models. While uninterpretable to human eye, adding this pixel patch to every test image allows the frozen model to adapt better to a new task. We believe visual prompting aligns pre-trained and downstream distributions by converting the downstream dataset to look more similar to the pre-trained dataset. Under this hypothesis, visual prompting would not help for datasets already within the pre-trained distribution, yet could help significantly for datasets that are severely out-of-distribution, which may explain the performance gap between tasks.

![Figure 10: Visualizing task-specific visual prompts for each pre-trained model.](make this into pdf)