The Curious Robot: Learning Visual Representations via Physical Interactions

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Abstract. What is the right supervisory signal to train visual representations? Current approaches in computer vision use category labels from datasets such as ImageNet to train ConvNets. However, in case of biological agents, visual representation learning does not require semantic labels. In fact, we argue that biological agents use active exploration and physical interactions with the world to learn visual representations unlike current vision systems which just use passive observations (images and videos downloaded from web). For example, babies push objects, poke them, put them in their mouth and throw them to learn representations. Towards this goal, we build one of the first systems on a Baxter platform that pushes, pokes, grasps and actively observes objects in a tabletop environment. It uses four different types of physical interactions to collect more than 130K datapoints, with each datapoint providing backprops to a shared ConvNet architecture allowing us to learn visual representations. We show the quality of learned representations by observing neuron activations and performing nearest neighbor retrieval on this learned representation. Finally, we evaluate our learned ConvNet on different image classification tasks and show improvements compared to learning without external data.

Keywords: manipulation, grasping, pushing, tactile sensing, visual representation learning

1 Introduction

In the last decade, significant advances have been made in the field of computer vision. One of the major reasons behind this success has been the shift from hand-designed features to feature learning. Much of the visual feature learning is done in a completely supervised manner using category labels. However, in case of biological agents, visual learning typically does not require categorical labels and happens in a completely “unsupervised” manner.

Recently there has been a strong push in learning visual representation without any category labels. Some recent approaches in this direction have considered using context from images, different viewpoints from videos, ego-motion.

1 By “unsupervised” we mean no supervision from other agents but supervision can come from other modalities or from time
Learning ConvNets from Physical Interactions: We propose a framework for training ConvNet using physical interaction data from robots. We first use a Baxter robot to grasp, push, poke and observe objects, with each interaction providing a training datapoint. We collect more than 130K datapoints to train a ConvNet. To the best of our knowledge, ours is one of the first systems which trains visual representation using physical interactions.

From videos [3] and generative models of images and videos [4,5,6,7], all the visual learning approaches still observe the visual world passively without any interaction with the world. On the other hand, visual learning in humans (or any biological agent) requires active exploration of the world. Our babies play with objects: They push them, grasp them, put them in their mouth, throw them etc. and with every interaction they develop a better visual representation.

In this paper, we break the traditional paradigm of visual learning from passive observation of data: images and videos on the web. We argue that the next step in visual learning requires signal/supervision from active exploration of our world. We build a physical system (on a Baxter robot) with a parallel jaw gripper and a tactile skin-sensor which interacts with the world and as it interacts more and more, it develops a representation for visual understanding. Specifically, the robot tries to grasp and push objects and observes haptic data by touching them and also explores different viewpoints of the objects. While there has been significant work in the vision and robotics community to develop vision algorithms for performing robotic tasks such as grasping, to the best of our knowledge this is the first effort that reverses the cycle and uses robotic tasks for learning visual representations.

We also propose a shared-ConvNet architecture where the first few convolutional layers are shared across different tasks, followed by 1-2 separate convolu-
tional and fully connected layers for each task. Since our architecture is shared, every interaction creates a data point to train this ConvNet architecture. This ConvNet architecture then forms the learned visual representation. Our active exploration data includes 40,287 grasps, 5,472 pushes, 1,372 tactile sensing observations and 84,430 pairs of different viewpoints of the same objects leading to more than 130,000 training datapoints for the ConvNet.

2 Related Work

Our work touches on two threads; how do you learn a representation in an unsupervised way, and how do you interact with the world for learning. We aim to unify these.

2.1 Unsupervised Learning

Unsupervised learning of visual representations is one of the most challenging problems in computer vision. There are two common approaches to unsupervised learning: generative and discriminative. In the generative framework, the core idea is to learn a model that can sample and generate new unseen images. Early work in this area focused on learning visual representations that (a) can reconstruct original images and (b) are sparse. This idea was extended by Hinton and Salakhutdinov [8] to train a deep belief network in an unsupervised manner via stacking layer-by-layer RBMs. Similar to this, Bengio et al. [9] investigated stacking of both RBMs and autoencoders. Recently, there has been a lot of success in the ability to generate realistic images. Some examples include the generative adversarial network (GAN) [5] framework and its variant including Laplacian GAN (LAPGAN) [6] and DCGAN [7].

The discriminative approach to unsupervised learning is training a network on an auxiliary task where ground-truth is obtained automatically (or via sensors). For example, Doersch et al. [1] presented an approach to train networks via supervision from context. The key idea is to sample pairs of patches from images and predict their relative spatial location. Other approaches such as [3,10] have tried to use videos and ego-motion to learn the underlying network. The key idea is to take pairs of frames from video and predict what camera motion led to the transformation. In another work, [2] tracks patches and uses the patches sampled from a track as a different viewpoints of same object instance and train an embedding network. Finally, our approach is also related to other efforts which train deep networks using supervision from other sensors such as Kinect [11,12] or motion information such as optical flow [13] since these approaches require manual labeling.

However, all the above approaches still only observe passive data. We believe active exploration: the ability to physically interact with elements of the scene, is a key requirement for training visual representations. In fact, this has been supported by several psychological behavior experiments as well [14].
2.2 Robotic Tasks

At the onset, we note that most work in this domain has been in using vision to solve a task. Here, we use these tasks to learn good visual representations. We design our experiments in which our robot interacts with objects with four different types of interactions.

**Grasping.** Grasping is probably the oldest problem in the field of robotics. A comprehensive literature review of this area can be found in [15][16]. Most work in this area has focused on using analytical methods and 3D reasoning for predicting grasp locations and configurations [17][18][19][20] but assume the availability of complete physical knowledge of the objects. However, recently data-driven learning-based approaches are starting to appear. Most initial work focused on using human annotators [21] but in this work we are more interested in building a self-supervision system [22][23][24][25]. For the purpose of this work we use the dataset provided in [25], since it is one of the biggest available datasets (and learning visual representations requires large amounts of data).

**Pushing.** The second task our system explores is the task of pushing objects. The origins of pushing as a manipulation task can be traced to the task of aligning objects to reduce pose uncertainty [26][27][28]. Furthermore, pushing actions can be used as a preceding realignment step before object manipulation [29][30]. The implementation of pushing strategies in the above mentioned work requires physics based models to simulate and predict the actions required to achieve a specific object goal state given an object start state. However, similar to grasping, in this work we are interested in self-learning systems which perform push interactions and use the sensor readings from robots as supervision.

**Tactile Sensing.** The third task we explore is tactile sensing: that is, a robot with a skin sensor touches/pokes the objects followed by storing skin sensor readings. We then try to use the sensor reading to provide supervision to train the visual representations. Highly sensitive tactile optical sensors have been used for robot exoskeletal finger feedback control [31]. While there have been approaches that have attempted to combine tactile sensing with computer vision for object detection [32], this is the first paper that explores the idea of learning visual representation from tactile data.

**Active Vision.** The final task we use our physical system for is to get multiple images of the same object from different viewpoints. This is similar to the idea of active vision [33][34]. However, in all the previous approaches the next best view is chosen after inference [34]. In this work, we sample thousands of such pairs to provide training examples for learning ConvNets.

**Vision and Deep Learning for Robotics.** There has been a recent trend to use deep networks in robotics systems for grasp regression [25][35][36] or learning policies for a variety of tasks [37][38]. For example, [39] show how deep visual features can be learnt for a state space representation of the environment and be used to perform manipulation tasks like scooping and pushing. In this paper, we explore the idea of using robotic tasks to train ConvNets as visual representation. We then explore the effectiveness of these for tasks such as object classification etc.
We now describe the formulation of the four tasks, namely grasping, planar push, poking (tactile sensing) and active vision for different viewpoints of the objects. We will describe the methodology of data collection, and an analysis of the deep network used in this work.

3.1 Planar Grasps

We use the grasp dataset provided in [25] for our experiments on the grasping task. The grasps present in this dataset are planar, i.e., the grasp configuration is along and perpendicular to the workspace. Hence the grasp configuration lies in 3 dimensions, \((x, y)\): position of grasp point on the surface of table and \(\theta\): angle of grasp. The dataset contains around 37K failed grasp interactions and around 3K successful grasp interactions as the training set. For testing, around 2.8K failed and 0.2K successful grasps on novel objects are provided. Some of the positive and negative grasp examples are shown in Figure 2.

Grasp prediction formulation: The grasp prediction problem can be formulated as finding a successful grasp configuration \((x_S, y_S, \theta_S)\) given an image of an object \(I\). However, as mentioned in [25], this formulation is problematic due to the presence of multiple grasp locations for each object and that ConvNets are significantly better at classification than regression to a structured output space. So, given an image patch an 18-dimensional likelihood vector where each dimension represents the likelihood of whether the center of the patch is graspable at \(0^\circ, 10^\circ, \ldots 170^\circ\). Therefore, the problem can be thought of as 18 binary classification problems. Hence the evaluation criterion is binary classification i.e. given a patch and executed grasp angle in the test set, predict whether the object was grasped or not.
Fig. 3. We detect an object and apply planar push (no force along gravity direction). Our push action is parameterized in terms of two 3D points: \(X_{\text{begin}}\) and \(X_{\text{final}}\).

### 3.2 Planar Push

We use a Baxter robot to collect push data as described in Figure 3. Given an object placed on the robot’s table and the model of the table, we perform background subtraction to determine the position of the object. After detecting an object using image \(I_{\text{begin}}\), we sample two points on the workspace: the first point is the start point \(X_{\text{begin}} = (x_{\text{begin}}, y_{\text{begin}}, z_{\text{begin}})\) from where the robot hand starts accelerating and gaining velocity. This start point is sampled from a Von Mises distribution to push the object towards the center of the robot’s workspace. We also sample another 3D point, \(X_{\text{final}} = (x_{\text{final}}, y_{\text{final}}, z_{\text{final}})\); this point defines the location at which the robot hand stops accelerating. Note that: (a) \(z_{\text{begin}} = z_{\text{final}}\) since we are dealing with planar pushing; (b) \(X_{\text{final}}\) and \(X_{\text{begin}}\) define both the direction and velocity/force with which the object is hit by the robot. Therefore, in this work, we parametrize push actions with 5 parameters: \((x_{\text{start}}, y_{\text{start}}, x_{\text{final}}, y_{\text{final}}, z_{\text{pushHeight}})\).

The robot takes the image \(I_{\text{begin}}\) of the object with the arms pulled back before the push action is executed. An off-the-shelf planner plans the push action \(X_{\text{begin}} \rightarrow X_{\text{final}}\). The arm retracts back and \(I_{\text{final}}\) is recorded after performing the straight line end effector action. We collect 5K push actions on 70 objects using the above described method. Some of these push actions are visualized in Figure 4.

**Push prediction formulation:** For incorporating learning from push, we build a siamese network (weights shared). One tower of siamese network takes \(I_{\text{begin}}\) as input and the other tower takes \(I_{\text{end}}\) as input. The two towers are then combined using fully connected layer to regress to what action caused this transformation. We remind that the push-action is parametrized by \(\{X_{\text{begin}}, X_{\text{final}}\}\). The loss function for regression is the euclidean loss. This action formulation captures the relevant magnitude as well as the localization and direction of the push.

### 3.3 Poking: Tactile Sensing

In this task, the robot pushes the object vertically into the table until the pressure applied on the object exceeds a limit threshold (as seen in Figure 5). A
random point is sampled inside the object as the poke location. This pressure is sensed by robust tactile sensors attached on the finger of the robot and is continuously recorded. On reaching the limit threshold, the arm pulls away from the object and repeats the motion for around 10 times per object. A total of 1K pushes are collected on 100 diverse objects.

The tactile skin-sensor used in this work increases its electrical resistance monotonically on the application of pressure. Hence an increase in pressure correlates to an increase in resistance which then correlates to an increase in voltage drop across the sensor. This voltage drop $p_{do}$ is sensed via an Arduino and logged with appropriate time stamps.

During poking, the pressure voltage data stream $p_{do}$ while pushing into the object is recorded. Some of this data is visualized in Figure 6. It can be noted how soft objects like the plush toy have a more gradual force response than harder objects like the hardcover book.

**Tactile prediction formulation:** The poke tactile prediction problem is formulated as a regression of the polynomial parametrization $P(p_{do})$ of the push action given the start $I_{begin}$ state of the object. Since a line parametrization works well to describe the push response (Figure 6), we use a linear parametrization making the problem a regression to two values (the slope and the intercept). Therefore, given an image of the object our ConvNet predicts the slope and the intercept of $P(p_{do})$. 

Fig. 4. Examples of initial state and final state images taken for the push action. The arrows demonstrate the direction and magnitude of the push action.
Fig. 5. The figure shows how the poke data with tactile sensing is collected. The profile of the tactile sensor tells us about the underlying material with which the object is made.

Fig. 6. Examples of the data collected by the poking action. On the left we show the object poked and on the right we show force profiles as observed by the tactile sensor.

3.4 Active Vision: Pose invariance data

Given the grasping and pushing tasks described above, pairs of images in any one task’s interaction contains images of objects with multiple viewpoints. The grasping dataset contains around 5 images of the object grasped from multiple viewpoints in every successful grasp interaction, while the planar push dataset contains 2 images of the object pushed in every push interaction. Figure 7 shows some examples of the pair of images of objects in different poses. In total, we use around 42K positive pairs of images and 42K negative pairs (images from different interactions).

Pose invariance formulation The pose invariance task is meant to serve as a supervisory signal to enforce images of objects in the same task interaction to be closer in fc7 feature space. The problem is formulated as a feature embedding problem, where, given two images, the distance between the features should be
small if the images are from the same robot interaction and large if the images are from different robot interactions.

3.5 Network Architecture

We now describe our shared network architecture for the four tasks described above. The network architecture used is summarized in Figure 8. The network exploits the hierarchical sharing of features based on the complexity of the task to learn a common representation at the root network. Hence our network architecture can be seen as a root network that learns from every datapoint presented with specialized task networks emanating from various levels. This is based on the insight that tasks which require simpler representations like the push action prediction should be predicted lower in the network than more complex tasks like object embedding. Specifically, push action needs pose-variance. However, more complex tasks like object embedding require the learning of pose invariant feature representations, which are usually learnt in the higher layers.

The tasks we deal with in this work require either one image as input (like the grasp prediction task and the poke tactile task) or two images (like the push action prediction task, the action invariance task). We however would like to learn a single root network for all these tasks. For this purpose the root network in both the streams for the two image tasks share parameters and are updated simultaneously. The gray blocks in Figure 8 show the root network which updates its parameters using loss gradients backpropagated from every task.

**Root Network** The root network follows the architecture of layer scheme of AlexNet [40] and can be seen as the gray network in Figure 8. The first convolutional layer (conv1) consists of 96 kernels with kernel size of $11 \times 11$. This convolutional layer and all the succeeding layers use a non linear Rectified Linear Unit (ReLU) as the transfer function. Local response normalization (LRN) is used and is followed by a spatial Max-Pooling (MP) of kernel size $3 \times 3$. This is followed by the second convolutional layer (conv2) that has 256 kernels of $5 \times 5$ kernel size and is followed by a LRN and a MP of $3 \times 3$. The third convolutional layer (conv3) has 386 $3 \times 3$ kernels which is followed by the fourth convolutional
layer (conv4) with $384 \times 3 \times 3$ kernels. The fifth convolutional layer (conv5), with $256 \times 3 \times 3$ kernels, is followed by a MP with a $3 \times 3$ kernel. The convolutional layers are followed by two fully connected layers (fc6 and fc7) that have 4096 neurons each and are each followed by a ReLU.

Since some tasks require two images as input, a clone of the root network is maintained with shared weights.

**Grasp Network:** The input to the grasp network (orange blocks in Figure 8) emanates from the conv4 output of the root network. This network passes the input through one convolutional layer (gr_conv1) with 256 kernels of $3 \times 3$ kernel size followed by a $3 \times 3$ MP. This then passes into a fully connected layer (gr_fc1) with 4096 neurons followed by gr_fc2 with 1024 and a final gr_fc3 with $18 \times 2$ neurons.

The error criterion used is the 18-way binary classifier used in [25]. Given a batch size $B$, with an input image $I_i$, the label corresponding to angle $\theta_i$ defined by $l_i \in \{0, 1\}$ and the forward pass binary activations $A_{ji}$ on the angle bin $j$ the loss $L$ is:

$$L = \sum_{i=1}^{B} \sum_{j=1}^{N=18} \delta(j, \theta_i) \cdot \text{softmax}(A_{ji}, l_i)$$

After an input training image $I_i$ is passed into the root network, the conv4 output is input into the grasp network that generates the classification loss that is backpropagated all through the chain. The weight update for the grasp network uses standard RMSprop, however the gradients for the root network are stored in memory and waits to be aggregated with the gradients from the other tasks.

**Push Network:** The input to the push network (blue blocks in Figure 8) emanates from the conv3 output of the root network. This network consists of one
convolutional layer (pu_conv1) with 48 kernels of $3 \times 3$ kernel size, a fully connected layer (pu.fc1) with 1024 neurons and a final fully connected layer (pu.fc2) with 5 neurons corresponding to the size of the action prediction. Since the input for the push task is two images, the outputs from the pu_conv1 for both the images are concatenated to result in a 96 dimensional feature map that is fed into pu.fc1. A mean squared error (MSE) criterion is used to provide the loss for this task.

Given input images $I_{\text{begin}}$ and $I_{\text{final}}$, $I_{\text{begin}}$ is passed in the root network while $I_{\text{final}}$ is passed through the clone of the root network. The conv3 outputs from both the networks pass through two copies of pu_conv1 which is then concatenated and passed through the push network to generate MSE regression loss. The loss is backpropagated through the chain, with the weights in the push network getting updated in the batch using RMSprop while the gradients in the root network are stored in memory to be aggregated later. For the weights in pu_conv1, the gradients are accumulated and mean-aggregated before an update.

**Poke Network:** The input to the poke network (green in Figure 8) emanates from the fc6 of the root network. The poke network then passes the input into a fully connected layer po.fc1 with 512 neurons followed by po.fc2 with 2 neurons as the tactile prediction. The MSE criterion is used to provide the regression loss for this task.

Given an input training image, it is first passed through the root network. The fc6 output is then fed as an input to the poke network that makes a tactile prediction. The loss from the MSE criterion is backpropagated through the chain, with the weights of the poke network getting updated with every batch using RMSprop while the gradients in the root network are stored in memory to be aggregated later.

**Action Similarity Embedding:** Feature embedding is done via a cosine embedding loss on the fc7 feature output. Given a pair of images, one is passed through the root network while the other is passed through a clone of the root network. The cosine embedding loss on the fc7 feature representations are then backpropagated through the chain and the gradients for the two copies are accumulated and mean aggregated.

**Training Details:** We follow a two-step training procedure for the network. In the first stage, we first initialize the root network (upto conv4) and the grasp network with Gaussian initialization. We train only the grasp network and the lower root network for 20K iterations on the grasp data.

In the second stage, we create the full architecture with first conv4 copied from the grasp learning. Then, batches with size of 128 are prepared for each of the 4 tasks and are sequentially input into the network. Weights for the grasp, push and poke networks are updated during their respective backward propagation cycles, while the gradients for the root and the clone network are accumulated until one batch for each of the tasks is complete. After one cycle of the 4 task batches, the accumulated gradients for the root and clone network are mean aggregated and a weight update step is taken. RMSprop is used as the optimizer for all the networks.
The learning rates used for the root, the grasp, the push and the poke networks are $2e^{-6}$, $1e^{-4}$, $1e^{-2}$ and $1e^{-2}$ respectively. These values are empirically found by network convergence on the training data. Learning rate decay of 0.97 is performed after 10 epochs of iterations on the network’s respective data.

4 Results

We now discuss our experimental results and demonstrate the effectiveness of learning via physical interactions. First, we analyze the learned network in terms of what it has learned and how effective the feature space is. Next, we evaluate the transferability of learned representations to other tasks by finetuning it for tasks such as image classification.

4.1 Analyzing the ConvNet

As a first experiment, we visualize the maximum activations of neurons in layer 4 and layer 5 of the network. Specifically, we run our learned network on 2500 ImageNet images corresponding to household items and find the images that maximally activates different neurons. We show these maximally activated images along with the receptive fields for some conv5 and conv4 neurons of our root network in Figure 9. Notice that conv5 is able to correlate strong shape attributes like the spherical objects in row 4, the cereal bowls in row 5 and the circular biscuits in row 3. This is quite intuitive since tasks such as pushing, grasping etc. are functions of the object shapes.

As a next experiment, we analyze the learned network without fine tuning for the task of nearest neighbor. We use 25 household objects as query images and 2500 ImageNet images as the training database. We use the root network’s conv5 feature space to perform nearest neighbors (See Figure 10). Again as expected the nearest neighbors seem to be based on shape attributes.

4.2 Classification on ImageNet Household

For analyzing the effectiveness of our learned visual representation, we would like to analyse the root network of our learnt robot task model on ImageNet categories. However ImageNet image categories are of a wide variety while the image data the robot sees is mostly of objects on a tabletop setting. Hence for a more reasonable study we report results on a dataset containing 25 object synsets: atomizer, ball, biscuit, bomb, bottle, bowl, box, chalk, cup, device, hook, marker, pen, plush, rod, shaker, sharpener, sponge, spoons, spray, stapler, swatter, tool, toys and vegetable. Since some of these synsets contain very few images, 100 images from each of these are accumulated to make a 2500 image dataset.

Classification: Results of classification accuracy on this dataset can be found in Table 1. It is noteworthy that our network, finetuned on this 25 class dataset, gives around 33.5% accuracy which is 8.5% higher than training from scratch.
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**Fig. 9.** The maximally activating images for the conv5 and conv4 neurons of our root network is shown here. The conv5 is able to correlate strong shape attributes like the spherical objects in row 4, the cereal bowls in row 5 and the circular biscuits in row 3.

This means that our network learns some generalized features from the robot task training data that helps it perform better on the ImageNet task. This is quite encouraging, since to the best of our knowledge, the correlation between robot tasks and semantic classification tasks have been assumed for decades but never demonstrated.

| Table 1. Classification on ImageNet Household |
|---------------------------------------------|
| Root network with random initialization     | 25.1 |
| SVM over HoG features                       | 26.8 |
| Root network pretrained on robot tasks (ours)| 33.6 |

4.3 Other datasets

We also evaluated the performance of our learned ConvNet on the UW RGB-D dataset [42], which consists of 300 objects belonging to 51 categories. Each object is accompanied by images of the object at different viewpoints. During training one object from every category is put in the test split. We report an
Fig. 10. The first column corresponds to images for which the nearest neighbours in conv5 feature space are presented in the corresponding row. Note that the nearest neighbours work well for images with less background clutter like the spray bottle in the 4th row. Also, the network learns that cups and bowls are similar (row 5).

Table 2. RGB-D Object Category Recognition

|                                | accuracy (%) |
|--------------------------------|--------------|
| Root network with random initialization | 46.8         |
| Root network pretrained on robot tasks (ours) | 58.7         |
| ImageNet trained AlexNet          | 78.9         |

average accuracy of 49.3% on the splits provided, which is about 5% higher than learning from a scratch network.

Finally, we evaluated our representation on Caltech-256 dataset. Compared to the scratch which has a performance of 24.2%, we have an accuracy of 29.4% compared to ImageNet pretrained performance of 65.6%.

5 Conclusion

We present a method of learning visual representation using only robot interactions with the physical world. By experiencing over 130K physical interaction data points, our deep network is shown to have learned a meaningful visual representation. We visualise the learned network and perform classification tasks to validate our hypothesis. We note that this is just a small step in starting to integrate robotics and vision closely together.
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