Abstract—Good prediction is necessary for autonomous robotics to make informed decisions in dynamic environments. Improvements can be made to the performance of a given data-driven prediction model by using better sampling strategies when collecting training data. Active learning approaches to optimal sampling have been combined with the mathematically general approaches to incentivizing exploration presented in the curiosity literature via model-based formulations of curiosity. We present an adversarial curiosity method which maximizes a score given by a discriminator network. This score gives a measure of prediction certainty enabling our approach to sample sequences of observations and actions which result in outcomes considered the least realistic by the discriminator. We demonstrate the ability of our active sampling method to achieve higher prediction performance and higher sample efficiency in a domain transfer problem for robotic manipulation tasks. We also present a validation dataset of action-conditioned video of robotic manipulation tasks on which we test the prediction performance of our trained models.

I. INTRODUCTION

Prediction models are required for robotic planning and control in dynamic environments. To choose the correct actions to accomplish specific tasks, anticipating the outcomes of actions before they are taken is necessary. These predictions can be generated by models whose parameters are estimated from sampled sensory data. The sampling strategy for collecting this data strongly impacts the realized model performance. In particular, models without global convergence guarantees will not always converge to the same parameterization with different sampling strategies, and even models with global convergence guarantees will converge at different rates depending on the selection of samples. In this work, we present a novel method for sampling data to train a vision-based action-conditioned prediction model. We demonstrate that using our sampling approach achieves faster convergence and better prediction performance than models trained with data sampled with existing strategies.

Good prediction models are generalizable and transferable in addition to being able to accurately model the system and environment. Good models not only give accurate predictions but are also able to do so with high sample efficiency. The generalization capabilities of these models should allow for similar quality of prediction in scenarios beyond those seen in the training data. Furthermore, prediction models used for robotic planning and control should not be strongly tied to a particular experimental setup. For example, it is desirable for prediction models to be transferable across similar laboratory environments and maintain a comparable level of performance. Additionally, prediction models should ultimately be able to transfer across similar robotic platforms.

Predicting well is challenging due to the inherent tradeoffs present between desirable model properties including sample efficiency, generalizability, transferability, and accuracy. For example, if a model is specialized to be more accurate, it may lose transferability. While building better prediction models is perhaps the most intuitive approach for improving prediction, creating more effective sampling strategies can improve prediction in a manner which avoids compromises in model design. The active learning and active perception literature has long established the ability of good sampling strategies to increase sample efficiency and model performance [48, 15, 5, 10, 72]. Robotic learning has more recently demonstrated the ability of high-dimensional data-driven methods to transfer across platforms by sampling a small collection of data in the new domain [16]. However, in this class of robot learning problems, only random sampling is currently used to select samples in the new domain. In this work, we show that a targeted sampling approach based on maximizing a curiosity-driven objective, leads to sample efficient prediction performance improvements in a domain transfer problem, as illustrated in Figure 1.

Methods for curiosity incentivize exploration based on expected information gain (typically via mathematical proxies)
which can be used to perform targeted sampling [51, 52, 53, 32]. Many of the curious strategies for exploration incorporate perception-based prediction models [47, 11]. However, these formulations of curiosity are structured as a reward derived after the action taken and thus require knowledge of the action outcome. This methodological approach necessitates integration with model-free reinforcement learning in which rewards provide feedback to an updated policy for selecting actions. In contrast, model-based methods use a prediction model directly to select actions, so curiosity measurements must be made before the action is taken to execute curious behavior. The fundamental difference between these approaches is visualized in Figure 1.

In work most similar to our own, Shyam et al. [60] provides an approach to computing certainty of model predictions before taking the chosen action in a model-based approach to curiosity. This computation is derived from the variance of outcomes computed within an ensemble of prediction models. The action resulting in the highest variance of outcome expectations is taken. Our formulation of model-based curiosity uses an objective based on maximizing a score given by a discriminator network in order to choose actions which result in outcomes considered the least realistic by our adversarial network. Our method integrates with model-based reinforcement learning via a more computational efficient measurement for curiosity.

When our prediction model is trained on sampled data, evaluation cannot be performed on held out samples from this collection. Validation results will be biased toward successful prediction of the sequences of observations and actions collected with the policy on which the model was trained. However, the target of these models is to predict behavior in robotic tasks though training directly on those tasks does not allow for good generalization performance. In this work, we focus our experiments on robotic manipulation. Thus, we present a validation dataset of robotic manipulation tasks on a Baxter robot platform in domain transfer experiments.

In summary, we present the following contributions toward improving prediction for robotic manipulation tasks.

1) Adversarial curiosity objective compatible with model-based reinforcement learning systems.

2) Method for active learning using our curiosity approach as an objective for the cross-entropy method with high-dimensional input from images.

3) Demonstration of increased prediction performance and increased sample efficiency of models trained with samples from our curiosity strategy collected on a Baxter robot platform in domain transfer experiments.

4) Dataset of action-conditioned video sequences of robotic manipulation tasks on a Baxter robot for model validation.

Our paper is organized as follows. First, we review the literature on sampling with both curiosity and active learning methods. Then, we present our adversarial curiosity objective for sampling in a model-based reinforcement learning problem. Next, we both motivate the robot manipulation problem used in our experiments and specify the model and planner used in our reinforcement learning setup. In our results, we present an analysis of the samples collected by our curious policy compared to the randomly sampled data. Finally, we present the dataset we built for prediction validation, and compare our prediction results for the models trained on the data sampled with the curious and random policies.

II. RELATED WORK

We specify our method as an adversarial curiosity objective which we use to perform active learning in model-based reinforcement learning. Thus, we contextualize our work in the active learning and curiosity literature. The goal of both active learning and curiosity is to provide a method of selecting samples with which to train a model such that the model gains the most possible information from the sampled data.

Model-Free Curiosity Several existing models use exploration incentives to estimate and seek visual novelty in model-free reinforcement learning. Approaches include generalizing count-based exploration to continuous domains [9, 45], rewarding the policy based on the observed error in a prediction model [46, 12, 11], rewarding the policy based on the disagreement in an ensemble [44, 47], and rewarding the policy based on information gain in a Bayesian neural network [30]. We present a model-based curiosity method using a discriminator network. This construction enables our objective to be trivially modified to provide reward-based feedback on sampled instead of predicted trajectories. However, we do not formalize or experimentally evaluate model-free methods in this work.

Model-Based Curiosity There are far fewer model-based curiosity methods than model-free. Discrete count-based methods [56], estimate the learning progress of a potential sample [41]. Shyam et al. [60] uses ensembles of models to estimate uncertainty in predictions. Bechtle et al. [8] minimizes the uncertainty of Bayesian models. Our work differs from previous model-based active exploration methods in that it is able to operate computationally efficiently in high-dimensional
continuous domains through the use of a discriminator which provides scores for the realism of our model predictions.

Adversarial Curiosity The concept of adversarial curiosity was first proposed by Schmidhuber [55] prior to the integration of curiosity with planning algorithms. This work suggested that the formulation of the minimax problem presented a method of encoding introspective behavior in a model. Schmidhuber [54] further argues that minimax optimization problems such as the one we propose here provide intrinsic motivation for a model to invent novel information about which to learn. This behavioral paradigm is considered a form of curiosity [51, 55, 54, 53, 32]. The explicit model of adversarial curiosity we propose leverages a discriminator network to give scores for measuring the certainty of our model predictions.

Active Learning Active learning is the process where a machine learning algorithm selects its training data to improve its data efficiency and performance [56]. Several approaches to active learning have been proposed, including sampling the most uncertain data points [40, 63, 57, 54, 71, 25], sampling where an ensemble of models disagrees [59, 14, 42, 26, 31, 47], sampling data that will cause the largest expected change in the model [58, 57, 61, 68], expected information gain [29], sampling data that will cause the largest expected error reduction [48, 43, 38]. Our approach is most similar to the works that sample the most uncertain data points.

Active Perception Active learning has been applied to perception, to allow an agent to select useful camera views [1] or learn their static and dynamic properties [3] by physically interacting with the world. Our work is most similar to [3] in that we are interested in learning the dynamics of objects by interaction, but instead of learning properties of specific objects, we are interested in learning a dynamics model that can fully predict future states.

III. Adversarial Curiosity Objective

Consider the dynamics of a system $\mathcal{F}$ mapping past states $I_t$ and actions $a_t$ to future states via

$$I_{t+1:t+T_j+1} = \mathcal{F}(I_{t:t-T_p}, a_{t:t+T_j}),$$

for $T_f, T_p > 0$ future and past time intervals, respectively. We then denote by

$$x = (I_{t:t-T_p}, a_{t:t+T_j}, I_{t+1:t+T_f+1})$$

any trajectory generated by system (1), and denote by $p(x)$ the distribution over these trajectories.

In our experimental setting (see Section IV), system states $I_t$ represent RGB images, and actions $a_t$ represent continuous controls inputs applied to a robotic arm. We note however that the method that we present next is completely general, and is equally applicable to continuous or discrete state and action spaces – although we foresee no conceptual or technical roadblocks in applying our method to other settings, we leave experimental validation to future work.

Our model-based curiosity method is defined in terms of the following three components:

i) A model $\mathcal{M}$ generates predictions of future states $\hat{I}$ given past states $I$ and actions $a$. These predictions are made over a prediction horizon $H$ using a set number of past context states $C$. Thus, our prediction model is given by

$$\hat{I}_{t+1:t+H+1} = \mathcal{M}(I_{t-C:t}, a_{t:t+H}).$$

To lighten notational burden going forward, we let $a := a_{t:t+H}, c := I_{t-C:t}$.

ii) A discriminator $D$, which assigns a score $s_t$ to each real trajectory $x$ generated by system (1) as well as imagined trajectories generated by the prediction model $\mathcal{M}$. To train the discriminator $D$, we solve the minimax optimization problem

$$\min_{\mathcal{M}} \max_D \mathbb{E}_{x \sim p(x)} [\log D(x)] + \mathbb{E}_{(c,a) \sim p(c,a)} [\log (1 - D(c, a, \mathcal{M}(c, a))].$$

The first term in the objective function of optimization problem (4) captures the ability of the discriminator to identify realistic trajectories generated by system (1), whereas the second term simultaneously reflects the predictive ability of the model $\mathcal{M}$, as well as the ability of the discriminator $D$ to distinguish between real and imagined trajectories.

The inner maximization trains the discriminator $D$ to differentiate between trajectories sampled from the data distribution $x$ and predicted trajectories $(c, a, \mathcal{M}(c, a))$. The outer minimization optimizes the performance of the prediction model $\mathcal{M}$. In summary, this minimax problem sets up a competition in which the prediction model tries to learn to make good enough predictions to fool the discriminator while the discriminator tries to improve differentiation of predictions from data samples.

After $D$ is trained, the discriminator scores for our imagined trajectories are evaluated as

$$s_t = D(c, a, \mathcal{M}(c, a))$$

and can be used as an uncertainty measure for the model predictions $\mathcal{M}(c, a)$.

iii) With these pieces in place, we can now define the curiosity based optimization problem that we solve in order to select action sequences that maximize a curiosity objective defined in terms of the discriminator score. In particular, we define a planner $P$ that selects actions
 which maximize the discriminator score by solving the optimization problem:

$$\mathcal{P}(c, a, \mathcal{M}, D) := \arg \max_a D(c, a, \mathcal{M}(c, a))$$  

(6)

It then follows that the actions resulting in the least realistic predictions are selected by the planner defined by optimization problem (6), resulting in qualitatively more curious behavior.

We note that in the domain transfer problem visualized in Figure 1 introduces a variant on this process for sampling. The model $\mathcal{M}$ is first trained jointly with the discriminator $D$ on data from Domain A. Then, the model $\mathcal{M}$ and the discriminator $D$ are used in the planner $\mathcal{P}$ to execute the sampling procedure in Domain B in order to gather data for updating $\mathcal{M}$. If the discriminator will continue to be used for future collection tasks, $D$ can be trained jointly with $\mathcal{M}$ again to be updated using the newly sampled data. This sampling procedure for domain transfer is laid out in more detail for our specific experimental application in Figure 3.

IV. EXPERIMENT DESIGN

To evaluate the performance of our sampling procedure to improve prediction, we consider a problem formulation in the robotic manipulation domain in which sample efficiency, generalizability, transferability, and accuracy are all evaluated. Here we motivate and specify this experimental design.

A. Motivation

The combination of action-conditioned prediction and model-predictive control (MPC) techniques have allowed for model based reinforcement learning to be applied to robotic [23, 22, 19, 20, 21, 13, 73, 70, 70, 50, 62] and simulated 27, 28, 55, 24 domains. These methods are trained with randomly collected 23, 22, 21, 13, 16, 24, 69, 27, 55, 62 data. Several modifications of these methods allow for learning from kinesthetic 70 or human 50 demonstrations. However, these kinds of data are expensive to collect in comparison to purely autonomous exploration. The most widely accepted approach, deep visual foresight, was proposed by 22, and has been used in many subsequent works 23, 19, 21, 20, 70, 16, 50, 62.

A standard approach to training and using pixel planning pipelines involves first collecting action-conditioned video data of a robot arm executing random motions in a bin of objects. These video sequences can be used to train a prediction model to gain a visual understanding of the dynamics of the robot, objects, and robot-object interactions. Then, this model can be used in robotic control to accomplish pixel-based goals via an objective function in the cross-entropy method. This control procedure is described further in Section VI-A.

Efforts have been made by robot learning researchers studying or using this class of video prediction models for robotic manipulation to release large scale video datasets of robots interacting with objects via a random policy for use in training 19, 20, 16. Leveraging this data to build new prediction models is challenging due to the differences between lab environments. For example, in each robot manipulation setup, lighting conditions, camera placement, and bin placement relative to the robot may vary. Recent work has shown the ability of models trained not only in different lab environments but also across different robot platforms to be able to effectively perform prediction in unseen environments and on held out platforms given fine-tuning on a small set of data collected on the target platform 16. This approach allows for dramatically decreased data collection overhead. However, given the need for small scale targeted data collection, more effective policies for collecting this set of data can be designed.

We consider this strategy of fine-tuning a prediction model from an externally provided dataset to be a strictly preferable approach to only training models with data collected on the target platform. Despite introducing domain transfer challenges, the expensive nature of data collection for this class of robot learning problems, the scale of data required to train these models, and the increasing availability of datasets provide strong incentives for this path. Thus, all prediction models following this framework must address the challenge of transferability. Furthermore, since the prediction models

*Image used with permission from 70
are trained on non-task specific object interaction, executing any manipulation tasks with this framework evaluates the generalizability of the models. A well-known challenge with this approach is the low sample efficiency of current solutions, so methods increasing sample efficiency in this space are very valuable. Finally, video prediction models which show improved generalizability and transferability over supervised approaches cannot achieve the accuracy of less general and transferable models.

Given the observations presented here, our robot manipulation problem has well-defined sample efficiency, generalization, transfer, and accuracy challenges. Thus, we use this problem as an experimental evaluation setting for our curious sampling procedure.

B. Prediction Model and Planner

In our experiments, we use a variant of the prediction model from Dasari et al. \[16\]. A stack of convolutional LSTMs is used to predict a flow field from an image \(I_t\) and action \(a_t\). This flow field is then applied directly to the input image \(I_t\) to predict the next image frame \(\hat{I}_{t+1}\). The true next image frame \(I_{t+1}\) is observed after the given action is taken. This network is optimized with an \(L_1\) loss between the predicted image \(\hat{I}_{t+1}\) and true image \(I_{t+1}\). In practice, these models perform predictions out to some horizon \(H\) using a context of \(C\) image frames in which the flow field estimates are applied recursively across the prediction horizon.

We extend the notation presented in Section \[III\] by setting
\[
\mathbf{h} = I_{t+1:t+H+1}
\]
(7)
such that a sampled trajectory is given by
\[
\mathbf{x} = (\mathbf{c}, \mathbf{a}, \mathbf{h}) = (I_{t-C:t}, a_{t+1:t+H+1}, I_{t+1:t+H+1})
\]
(8)

In the training procedure described by Step 1 in Figure \[3\] our prediction model is optimized jointly with the discriminator defined in Section \[III\] The optimization problem solved by our model \(\mathcal{M}\) during training is
\[
\min_{\mathcal{M}} \max_{\mathcal{D}} \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})} [L_1(\mathbf{h}, \mathcal{M}(\mathbf{c}, \mathbf{a}))] + \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})} [\log \mathcal{D}(\mathbf{x})] + \mathbb{E}_{(\mathbf{c}, \mathbf{a}) \sim p(\mathbf{x})} [\log (1 - \mathcal{D}(\mathbf{c}, \mathbf{a}, \mathcal{M}(\mathbf{c}, \mathbf{a})))].
\]
(9)

which combines the adversarial minimax game from equation \(4\) with the \(L_1\) loss on prediction error. This is similar to the loss in \[39\], where the combination of prediction error and an adversarial loss were shown to improve prediction quality and convergence.

We use this prediction model together with the cross-entropy method (CEM) \[49\] for planning. CEM has demonstrated success in planning directly from image data \[22,23,21,16,70,50\]. CEM estimates the solution of our curiosity objective from equation \(6\) via importance sampling. Action samples are selected from probability distributions of actions at each time step \(p(\alpha_{t,j})\). In our notation, \(\alpha_{t,j}\) is a distribution of actions. Similarly, \(\mathbf{I}_{t,j}\) is a distribution of predicted future states. Furthermore, \(t\) is the time of the current system state and \(t,j\) denotes an offset of \(j\) from time step \(t\). We introduce this notation for the prediction rollouts used by CEM since \(p(\alpha_{t,j}) \neq p(\alpha_{t+1,j-1})\) in general.

The probability distributions of the actions are recursively computed by the discriminator score of the predicted trajectory as follows
\[
p(\alpha_{t,j}) \approx \mathcal{D}(\mathbf{I}_{t,j}, \alpha_{t,j}, \mathcal{M}(\mathbf{I}_{t,j}, \alpha_{t,j}))
\]
subject to \(\mathbf{I}_{t,j} = \mathcal{M}(\mathbf{I}_{t,j-1}, \alpha_{t,j-1})\)
(10)
for \( j \in [1, H] \) and \( t \geq 0 \) with initial condition
\[
p(\alpha_{t,0}) \approx D(I_t, \alpha_{t,0}, \mathcal{M}(I_t, \alpha_{t,0}))
\]
subject to \( \hat{I}_{t,1} = \mathcal{M}(I_t, \alpha_{t,0}) \).
\( \text{(11)} \)

With our curiosity objective, the action sequence with the maximum score computed by our discriminator is selected by CEM and executed on the robot.

V. SAMPLING ANALYSIS

We evaluate the ability of our curiosity objective to effectively explore the environment by comparing the behavior of our curious policy to the behavior of the random policy used in prior work. To make this comparison, we execute Steps 1 and 2 visualized in Figure 3. First, our prediction model and discriminator is jointly trained on Sawyer data from the RoboNet dataset by optimizing equation (9). Then, we use each policy to separately sample trajectories on a Baxter robot platform. Our curious policy was able to visit a more diverse array of states and grasp more objects than the existing random policy.

Our policy is able to significantly increase the quantity of objects that the robot grasps. Since the interaction between the robot and objects are some of the most difficult things to predict in the tabletop manipulation setting, having more data about robot-object interactions makes a collected data set more effective. Examples of trajectories collected by our curious policy are shown in Figure 4.

Our curious policy also explores a larger distribution of the state space. Figure 5 shows a heatmap of the amount of time the robot’s end effector spends at each location in the xy-plane. The curious policy explores the more interesting regions of the state space, such as the edges of the bins. The walls of the bin are interesting because they block the motion of objects, causing the objects to have more complicated dynamics than when they are in the center of the bin.

In addition to exploring regions of the state space with more complicated dynamics, the curious policy also allows the robot to grasp objects more frequently. Figure 5 shows a histogram of when the grippers of the robot experienced non-zero forces during data collection for both the curious and the random policies. Non-zero forces indicate that an object is between the grippers, preventing them from fully closing. When following the curious policy, the robot spends a larger portion of its time grasping objects.

VI. PREDICTION RESULTS

We now demonstrate the ability of the samples collected with our curious policy to enable better prediction on the collecting robot than samples collected with our random policy. We are not able to perform prediction validation using held-out samples collected with a curious or random policy since the prediction performance of the model will be biased toward the validation set constructed using the same policy executed in the training data. However, the prediction model and data we use in our experiment are designed for executing pixel-based planning tasks. Therefore, we build a dataset for validation of manipulation task execution on our Baxter robot platform. We use this dataset to evaluate prediction performance on held out tasks. We find that the models trained on samples collected with the curious policy outperforms the models trained on...
A. Robot Manipulation Task Dataset

We execute two rounds of tasks on our Baxter robot platform: one round using the model trained with the curious policy and one round using the random policy. Though we are not directly using policy for control, we ensure the data collection is balanced between the two trained models to remove potential implicit bias.

Control experiments are executed by specifying a start location pixel on an object and a goal pixel in image space as visualized in Figure 7. The workspace for both the training data and control experiments is setup with a ring of cameras around the state space in which the robot can act. While the prediction model is trained with data from all viewpoints, samples collected with the random policy with lower sample complexity.

B. Prediction Model Results

We perform validation of our prediction model trained with each policy using our Robot Manipulation Task Dataset. Qualitative prediction results are shown in Figure 11. The model trained with the curious data more accurately tracks the position of the object.

The $L_2$ error of the prediction model trained with different numbers of samples from each policy is shown in Figure 9. The performance difference is further visualized in Figure 10 which shows the $L_2$ error improvement for the model trained with the data collected with the curious policy at different numbers of samples. The curious sampling strategy enabled an improvement in prediction over models trained with randomly sampled data by more than the standard error on all but one quantity of samples. Error improvement for the curious policy is especially pronounced at lower numbers of samples, probably because the random exploration policy is able to eventually stumble upon the more difficult data points that the curious model explicitly seeks out.

Dasari et al. [16] showed that training prediction models with all viewpoints improves performance over training with a single viewpoint in control executed with a single viewpoint.
Quantitative comparisons with additional metrics between models trained with data collected from random and curious policies are shown in Table I. The models trained with data collected with a curious policy outperform the models trained with data collected with a random policy across all metrics and over all numbers of samples.

Figure 8 shows the \( L_2 \) error on various samples for models trained with data collected under curious or random policies. By averaging the \( L_2 \) error of both models on a given sample, we were able to approximate the difficulty of predicting a the trajectory. Both models give similar qualities of predictions on the easier trajectories, but the model trained with data collected by the curious policy performs noticeably better on the more difficult trajectories. This shows the advantage of our curiosity formulation which explicitly seeks out the most difficult data points to sample.

**VII. Conclusion**

We presented a model-based curiosity approach to actively sample data used to train a prediction model. Our method maximizes an objective given by the score from a discriminator network to choose the sequence of actions that corresponds to the least realistic sequence of predicted observations. We showed that the samples collected by executing the action sequences generated by our new method increased coverage of our state space and increased object interaction. We also demonstrated increased prediction performance and decreased sample complexity in a domain transfer problem for robotic manipulation by using our targeted sampling strategy. To execute these experiments, we built a dataset for validation of action-conditioned video of robot manipulation tasks.

We note that the formulation of our method is fairly general. However, here we only demonstrate results and explain the formulation of this sampling strategy with one planning and prediction method combination. In future work, we will integrate this adversarial form of model-based curiosity with other planning and prediction methods for robotic manipulation and analyze how those decisions impact sampling performance.

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APPENDIX A
EXPERIMENTAL DETAILS

Additional visualizations of our results are available on our website at https://sites.google.com/view/action-for-better-prediction.

Since our video prediction model only runs on a single camera’s video stream, and our data collection setup had multiple cameras, our algorithm changed which camera it was using to plan after every trajectory. The hyperparameters for our planner are shown in Table II and III. The hyperparameters for our prediction model are shown in Table 12.

| Hyperparameter                                | Value |
|-----------------------------------------------|-------|
| Trajectory length                             | 30    |
| Robot actions per planning interval           | 10    |
| CEM iterations                                | 3     |
| CEM candidate actions per iteration           | 200   |
| CEM selection fraction                        | 0.05  |

**TABLE II**
HYPERPARAMETER VALUES FOR THE PLANNER DURING EXPLORATION

| Hyperparameter                                | Value |
|-----------------------------------------------|-------|
| Trajectory length                             | 10    |
| Robot actions per planning interval           | 10    |
| CEM iterations                                | 3     |
| CEM candidate actions per iteration           | 600   |
| CEM selection fraction                        | 0.05  |

**TABLE III**
HYPERPARAMETER VALUES FOR THE PLANNER DURING TASK EXECUTION

| Hyperparameter                                | Value |
|-----------------------------------------------|-------|
| Schedule sampling k                           | 4000  |
| Context Frames                                | 5     |
| Encoder Filters                               | [128, 256, 256] |
| LSTM Filters                                  | 256   |
| Decoder Filters                               | 256   |
| Discriminator Kernel size                     | [3, 4, 4] |
| Discriminator nonlinearity                    | Leaky ReLU |
| Discriminator Filters                         | [64, 128, 256, 256] |
| Discriminator training threshold              | 0.75  |
| GAN weight                                    | 0.001 |
| L1 weight                                     | 1.0   |
| Optimizer                                     | Adam [37] |
| Learning rate                                 | 0.0001|
| Beta1                                         | 0.9   |
| Beta2                                         | 0.999 |

Fig. 12. Prediction model hyperparameter values.