Procedure Planning in Instructional Videos

Chien-Yi Chang, De-An Huang, Danfei Xu, Ehsan Adeli, Li Fei-Fei, Juan CarlosNiebles
Department of Computer Science, Stanford University
{cy3, dahuang, danfei, eadeli, feifeili, jniebles}@cs.stanford.edu

Abstract

We propose a new challenging task: procedure planning in instructional videos. Unlike existing planning problems, where both the state and the action spaces are well-defined, the key challenge of planning in instructional videos is that both the state and the action spaces are open-vocabulary. We address this challenge with latent space planning, where we propose to explicitly leverage the constraints imposed by the conjugate relationships between states and actions in a learned plannable latent space. We evaluate both procedure planning and walkthrough planning on large-scale real-world instructional videos. Our experiments show that we are able to learn plannable semantic representations without explicit supervision. This enables sequential reasoning on real-world videos and leads to stronger generalization compared to existing planning approaches and neural network policies.

1 Introduction

Humans possess a natural ability of planning and reasoning to assist everyday tasks. We are able to picture what effects our actions would have and plan multiple steps ahead to achieve the intended goal. Take making an omelette in Figure 1 as an example: We understand the final omelette is cooked and has mushrooms. By reasoning about the effects of our actions, we can plan a cooking procedure where we first cook the eggs in a pan and then add mushrooms to it. This ability to plan and reason is key for an intelligent agent to fully automate real-world tasks such as cooking or assembly.

The procedure we have just described involves two key components: (i) visually understanding the goal state (i.e., cooked, has mushrooms) and the current state (i.e., raw), (ii) planning in this semantic space of object states to derive the sequence of actions to achieve the goal. While the two steps have been studied separately in visual state understanding [3] and task planning [6], simultaneously addressing both in real-world instructional videos remains unsolved. The key challenge of the task described in Figure 1 is the open-vocabulary [5, 7, 25] state and action spaces in real-world instructional videos. For example, the current observation can also be described as having eggs in a bowl. One can imagine an indefinitely growing semantic state space, which prevents the application of classical symbolic planning approaches [6] that require a given set of predicates for a well-defined state space. This challenge is amplified by the fact that we do not assume to know the effects of all the possible actions. How does the agent know that pouring the eggs to the pan will make it cooked? Without this knowledge, it is impossible to perform planning in the space.

We address this challenge by leveraging recent progress on latent space planning [19] and learning plannable representations [14]. In this case, we do not need to explicitly enumerate the open-vocabulary state space. Instead, the state space is captured by a latent state representation. In addition, the latent space is also plannable in a sense that the actions can be formulated as matrix transformations in the space, and thus enable the search of a sequence of actions to achieve the latent goal state. By formulating the actions as transformations in the latent space, we no longer require the explicit definition of their effects.

Preprint. Under review.
The primary technical challenge is that we have no direct constraints for neither the latent state space nor the action transformation in this space. In previous work, either there exists a strong correspondence between the visual space and the latent space so they can learn the latent space directly, or the action space is differentiable so it is possible to learn both the latent space and the transformations with gradients. In contrast, all we have is that the latent space should be plannable with respect to the transformations parameterized by the open-vocabulary, discrete actions. Without proper constraints, the optimization can easily lead to trivial latent space and action transformations.

Our solution is to leverage the conjugate relationships between states and actions. Instead of just treating the action as the transformation in the state space, the state also contains the history of previous actions and serves as the precondition for the next action. Given the action just performed, the state space should also be informative to the next possible actions. Similar ideas have been leveraged in the conjugate task graph approaches to improve the planning efficiency. Our approach provides an effective constraint on the learning of the latent space and the action transformation.

We evaluate our approach on real-world instructional videos. We show that the learned latent space can plannable representations are effective for planning in this challenging setting and significantly outperforms existing planning approaches in videos. As we have learned the mapping from the visual space to the latent plannable representation, we can further leverage this mapping to perform walkthrough planning and output the missing video clips between the start and the goal video clips. We further show that the use of explicit sequential reasoning allows our model to generalize to variations of the start and goal observations.

2 Related Work

Planning in Videos. In the planning literature, most studies rely on a prescribed set of state and action representations and symbols for the task. We are interested in works that perform planning in the visual space without well-defined state and action spaces. In addition, the complexity of instructional videos prevents the direct application of approaches that aim to plan directly in the visual space. In addition to the unsupervised and semi-supervised approaches, Universal Planning Networks use a gradient descent planner to learn representations for planning. However, it assumes the actions space to be differentiable. Alternatively, one can also learn the latent dynamics by optimizing the data log-likelihood from the actions. We use a similar formulation and further propose the conjugate constraints to expedite the latent space learning. Without using explicit action supervision, causal InfoGAN extracts state representations by learning salient features that describe the causal structure of the data in simple domains. In contrast to InfoGAN, our model operates directly on high dimensional video demonstrations and handle the semantics of actions with sequential learning.

Visual Prediction. Our planning tasks are related to visual prediction works because we both aim to recover the actions/videos that are not observed. Directly predicting the pixels or features is constrained to a short-horizon. On the other hand, anticipating a sequence of actions can go up to a few minutes. The main difference is that in our tasks the predicted sequence has
to reach the predefined goal. This poses a high standard on the quality of the learned prediction model. We address this challenge by leveraging conjugate constraints to learn the transition dynamics.

**Instructional Videos.** There has been growing interest in analyzing instructional videos. As a result, high-quality instructional video datasets with rich annotations have been curated\cite{21,26,27}. This opens the opportunities of addressing challenging tasks on real-world videos, including temporal segmentation and captioning\cite{20,26}, state understanding\cite{3}, and reference resolution\cite{10}. In this work, we introduce the new challenging planning tasks in instructional videos, which requires visual prediction, state understanding, and explicit sequential reasoning.

3 Method

We are interested in planning in real-world instructional videos. The key challenge is that both state and action spaces are open-vocabulary. We take a latent space approach by learning plannable representations of the visual observations, along with the action transformations in this space. We will first define the procedure planning problem setup and how to address it using a latent space planning approach. We will then discuss how we learn the latent space and leverage the conjugate relationships between states and actions to avoid trivial solutions to our optimization. Finally, we will present the algorithms for procedure planning and walkthrough planning\cite{14} in the learned plannable space.

3.1 Problem Formulation

As illustrated in Figure 1, given the current observation $o_t$ and the goal observation $o_g$, both in the visual space, the objective is to output a sequence of actions $[a_t, \cdots, a_{t+h-1}]$ that can bring the underlying state of $o_t$ to that of $o_g$. Here, $h$ is the horizon of planning, which defines how many steps we allow the model to take. While one can directly learn a function from the observations $(o_t, o_g)$ to the intermediate actions, we argue and will show in our experiments that a better approach is to formulate it as a planning problem and perform explicit sequential reasoning.

Despite the advantages of formulating the problem as planning, it requires two components: (i) a mapping from the visual observation $o$ to a semantic state $s$ (e.g., from the observed frames to cooked eggs with mushrooms) (ii) the transition dynamics $P(s'|s, a)$ so that we can apply different actions and search for the goal $s_g$. The key challenge is that $s$ and $a$ are open-vocabulary and can be indefinitely large in instructional videos. We thus instead plan in a latent space $x = f(o)$ from the visual space. The only information we have about this space is that there exists a transition dynamics $T(x'|x, a)$. Given $f(\cdot)$ and $T$, we can find the plan $\pi = [a_t, \cdots, a_{t+h-1}]$ by (i) mapping from the visual space to the latent space $x_t = f(o_t)$, $x_g = f(o_g)$ and (ii) search in the latent space using $T(x'|x, a)$ to find the sequence of actions that can bring $x_t$ to $x_g$. We will discuss details of this procedure in Section 3.3.

3.2 Learning Plannable Representations from Real-World Videos

We have discussed how we can plan in real-world videos based on $T(\cdot|x, a)$ and $f(\cdot)$. One possible approach for learning $T(\cdot|x, a)$ and $f(\cdot)$ is to directly optimize $f(\cdot)$ with some surrogate loss function, such as mutual information\cite{14}, without considering $T$. This is not suitable for our case, because it assumes strong correspondence between $o$ and $x = f(o)$, while in real-world videos, a small change in visual space can induce a large change in the semantic space and vice versa. An alternative approach is to formulate a differentiable objective jointly with both $T(\cdot|x, a)$ and $f(\cdot)$\cite{19}. This also does not work for our case because it often requires the action space to be differentiable, while we have an open-vocabulary and discrete action space.

**Alternative Optimization.** Because of the above challenges, we propose to use the alternative optimization approach to iteratively learn $T(\cdot|x, a)$ and $f(\cdot)$. We assume we have the dataset $D = \{(o_t, a_t, o_{t+1})\}$, which is the visual observation, the action taken, and the corresponding next visual observation. The triplets can be parsed automatically from instructional videos. Given $D$, we can optimize for having $D$ given $T(\cdot|x, a)$ and $f(\cdot)$ by:

$$
L_T = \max(0, T(x_{t+1}|x_t, a_t) - T(x'|x_t, a_t) - \alpha) \quad (1)
$$

$$
= \max(0, T(f(o_{t+1})|f(o_t), a_t) - T(f(o')|f(o_t), a_t) - \alpha), \quad (2)
$$

3
We have discussed how we learn both the latent space and the transformations parameterized by the open-vocabulary actions in Section 3.2. Now we discuss how we leverage $\mathcal{T}(\cdot|x,a)$ and $f(\cdot)$ for planning in the latent space. In addition, as we have the mapping from the visual space to the latent space, we are able to perform walkthrough planning [14] given a pool of candidate visual states. As shown in Figure 1, walkthrough planning would output the intermediate video clips instead of the actions between the current observation and the goal. We will first discuss latent space planning and show how the same framework can also be applied to walkthrough planning.

**Procedure Planning.** We use a standard forward planning [6] based on $\mathcal{T}(\cdot|x,a)$ and $f(\cdot)$ to achieve the goal. Given the current and the goal observations $o_t$ and $o_g$, we first map them to the latent space with $f(\cdot): x_t = f(o_t), x_g = f(o_g)$. In contrast to symbolic planning, we do not have a list of applicable actions to apply in the search process. In this case, one additional advantage of having $\mathcal{P}$ is that we can actually sample the actions to apply using $\mathcal{P}(\cdot|a_{t-1}, x_t)$. Based on $a_t$ and $x_t$, we can obtain $x_{t+1}$ using $\mathcal{T}(\cdot|x,a)$. The search process continues for a max iteration of $\beta$ and threshold $\epsilon$. The procedure is shown in Algorithm [1]. In practice, the search is implemented by maintaining a heap of latent states based on the distance to the goal $x_g$ and prioritizing the ones closer to the goal.
Walkthrough Planning. Kurutach et al. [14] proposed walkthrough planning. Instead of outputting the plan \( \pi = [a_t, \cdots, a_{t+h-1}] \) between \( o_t \) and \( o_g \), walkthrough planning outputs the visual observations \( [o_{t+1}, \cdots, o_{t+h}] \) between \( o_t \) and \( o_g \). The outputs of walkthrough planning can serve as visual signal of the subgoal to guide the task execution. In addition, it is also helpful to visualize what the model has learned. Given the pool of visual observations \( \{o_i\} \), we can first construct the score matrix \( R[i, j] \) to capture the transition probability between two video clips \( o_t \) and \( o_j \) using our learned model \( \mathcal{T} \) and \( \mathcal{P} \). We can then perform walkthrough planning by finding the length \( h \) path that starts at \( o_t \) and ends at \( o_g \), while maximizing the total score. If the pool of video clips is all the clips in the same instructional video, then this is equivalent to finding a permutation function \( b : \{1, 2, \ldots, h\} \to \{1, 2, \ldots, h\} \) that maximizes the total score along the permutation path, under the constraints that \( b(1) = 1 \), \( b(h) = h \). The details of the process is shown in Algorithm 2.

4 Experiments

We aim to answer the following questions in our experiments: (i) Can we learn plannable representations from real-world instructional videos? How does it compare to existing latent space planning methods? (ii) How important are our conjugate constraints? (iii) Can we further retrieve intermediate visual subgoals using the same model? We answer the first two questions with ablation studies on challenging real-world instructional videos. In addition, we evaluate the generalization of our model to various start and goal observations. For the last question, we evaluate walkthrough planning [14] of our model and compare to the existing approaches.

Dataset. We use the CrossTask instructional video dataset [27] collected for 83 different tasks for our evaluations. The tasks include cooking tasks like Grill Steak, Make Pancakes, and non-cooking tasks like Change a Tire or Build Simple Floating Shelves. The 83 tasks are split into two parts: 18 primary and 65 related tasks, where the 65 related tasks are collected automatically without manual annotations. We use the 18 primary tasks for training and evaluation, where each video has been annotated with steps and their temporal boundaries.

Implementation Details. We use the features precomputed in the CrossTask dataset [27]. Each 3200-dimensional feature vector is a concatenation of the 13D, Resnet-152 and audio VGG features. The state mapping \( f \) and action embedding \( g \) are 128-dimensional. \( \mathcal{T} \) is a 2-layer MLPs with 128 units that takes the outputs of \( f \) and \( g \) as inputs. The network \( \mathcal{P} \) shares the state and the action embedding with \( \mathcal{T} \) and outputs an action instead of an embedding vector. In addition, we introduce recurrence to \( \mathcal{P} \) by replacing the MLPs by a recurrent neural network (RNN) of the same size, and concatenate the goal embedding as input. For training, we use Adam optimizer and learning rate of 0.0001. We schedule the learning rate to decay with a decay factor 0.5 and a patience epoch of 5.

4.1 Evaluating Procedure Planning

Experimental Setup. We divide the dataset by 70/30 splits on the instructional videos for training and testing. For each video, we use sliding windows to sample a fixed number \( h \) ( \( h = 4 \) or \( 5 \)) of consecutive video clips to generate training and testing data. The inputs to the models are the start video clip \( o_t \) and the goal video clip \( o_g \), and the goal is to output a sequence of \( h - 1 \) actions that brings \( o_t \) to \( o_g \). We use the action space from the CrossTask dataset [27] by enumerating all the predicates and objects, which is shared across all the tasks in the dataset.
Table 1: Results for procedure planning. Our full model significantly outperforms baselines. With around 10% improvement of accuracy, our full model is able to improve success rate by 8 times compared to Ours w/o T. This shows the importance of reasoning over the full sequence.

| h = 4 | Succ. Rate | Uniform | UPN [19] | Ours w/o P | Ours w/o T | Ours |
|-------|------------|---------|-----------|------------|------------|-------|
|       | Succ. Rate | <0.01%  | 2.89%     | <0.01%     | 1.35%      | 12.18% |
|       | Accuracy   | 0.94%   | 24.39%    | 2.61%      | 18.66%     | 31.29% |
|       | mIoU       | 1.66%   | 31.56%    | 0.86%      | 28.81%     | 47.48% |
| h = 5 | Succ. Rate | <0.01%  | 1.19%     | <0.01%     | 0.65%      | 5.97%  |
|       | Accuracy   | 0.83%   | 21.59%    | 2.51%      | 15.97%     | 27.10% |
|       | mIoU       | 1.66%   | 27.85%    | 1.14%      | 26.54%     | 48.46% |

**Baselines.** We compare with the following models:

- **Uniform Policy.** The uniform baseline randomly selects an action from the set of all actions. We use it as a lower bound of the performance.

- **Universal Planning Networks (UPN) [19].** UPN is the closest to ours among the existing works. We both aim to learn a plannable representation using supervision from the imitation loss function at training. However, UPN assumes a continuous and differentiable action space to enable gradient based planning, which might not be applicable to our discrete open-vocabulary action space.

- **Ours w/o T.** We compare to the ablation of our model without learning the transition dynamics T, where we only have P that aims to directly output the actions based on the previous action and the current state. We implement P with an RNN and also concatenate the goal as input. In this case, this ablation is equivalent to a goal-conditional RNN policy directly trained with expert actions.

- **Ours w/o P.** We compare to the ablation without the conjugate constraints for learning. In this case, the joint optimization of the transition dynamics T and the mapping f(·) to the latent space can easily overfit to the training trajectories.

**Metrics.** We use three metrics for comparison. The first is **success rate.** Although we do not have access to the underlying environment to evaluate the policies by executing them, we consider a plan as a success if all the actions in the plan are the same as those in the ground truth. This is a reasonable approximation because we consider a fixed number of steps, and there is less variation in the ways to complete the task. The second metric we consider is the accuracy of the actions at each step, which does not require the whole sequence to match the ground truth as the success rate, but only looks at an individual time step. We average over the actions to balance the effect of repeating actions. The final metric we use is mean Intersection over Union (mIoU), which is the least strict out of all the metrics. We compare the IoU by (\{a_t\} ∩ \{a^*_t\}) | \{a_t\} ∗ \{a^*_t\}, where \{a^*_t\} is the set of ground truth actions, and \{a_t\} is the set of predicted actions. We use IoU to capture the cases where the model understand what steps are required, but fails to discern the order of the actions.

**Results.** The results are shown in Table 1. UPN is able to learn representations that perform reasonably well compared to the uniform baseline. However, as the action space in instructional videos is not continuous, the gradient-based planner is not able to work well. This makes the UPN performs similar to Ours w/o T, which is like an RNN goal-conditional policy trained with imitation objectives. On the other hand, Ours w/o P cannot learn reasonable plannable representations without the conjugate constraints on the latent space. Our full model combines the strengths of planning and action imitation objective as conjugate constraints, which enables us to learn plannable representations from real-world videos to outperform all the baseline approaches on all metrics. One interesting observation is that although our full model only outperforms Ours w/o T by ∼ 10% in accuracy, it is able to significantly improve the success rate. This is because we explicitly perform sequential reasoning using T in our full model to find the sequence of actions to reach the goal and maximize the success rate. In contrast, Ours w/o T directly outputs the sequence of actions without explicit sequential reasoning. While UPN also aims to directly leverage goal in the algorithm, the non-differentiable action space prevents the success of gradient-based planning. Figure 3 shows the qualitative results of our procedure planning. The first row shows the 9 snapshot observations in making French toast. In the second row, we pick \(o_3\) and \(o_7\) as the start and goal observations and ask the model to plan for 4 actions in between. The model successfully recognizes that there are two French toasts and dip and pan fry the bread twice. In the third row, we change the goal to \(o_9\). In this...
Figure 3: Procedure planning qualitative results. The first row shows the 9 snapshot observations in making French toasts. Our proposed model is robust to changes of start and goal observations among different stages in the video, and is able to output reasonable plans to achieve the goal and reason about the essential steps.

4.2 Evaluating Walkthrough Planning

Given the start and goal video clips, we have shown that we are able to output a sequence of actions that brings the start to the goal. In this section, we show if the same model can be used to retrieve visual subgoals for task completion. The problem is referred to as walkthrough planning [14], where the objective is to output the waypoints between the start and goal observations.

Experimental Setup. In contrast to the videos studied in previous works [12, 14], the instructional videos we use in this paper is extremely challenging to generate using visual generator [14]. We bypass this scalability issue by providing a pool of candidate video clips. The model only needs to generate the lower dimensional features that can be used to retrieve the correct video clips. Specifically, we use all the video clips in the original video as the video clip pool. In this case, the task is the same as sorting the intermediate video clips while fixing the first and the last video clips.

Baselines. We further compare to the following approaches for walkthrough planning:

- Causal InfoGAN (CIGAN) [14]. CIGAN learns plannable representations by maximizing the mutual information between the representations and the visual observations. Additionally, the latent space is assumed to follow the transition dynamics of a certain class of actions. CIGAN is able to perform walkthrough planning and requires minimal supervision. As the instructional videos are hard to generate, we use CIGAN on the same features we use for a fair comparison.

- Visual Ordering (VO). As the task is reduced to sorting a pool of video clips, one baseline is to directly learn a model \( V(o_1, o_2) \) to see if \( o_1 \) and \( o_2 \) are consecutive video clips in the same video. Given \( V(o_1, o_2) \), we can find the order of video clips by maximizing the total score given by \( V \). We trained \( V(o_1, o_2) \) using the same setup as our \( T \), only that the actions \( a \) are not used as the input.

Metrics. Let \( Y = (y_1, ..., y_h) \) be a sequence of the ground truth order, and \( b : \{1, 2, ..., h\} \rightarrow \{1, 2, ..., h\} \) be the permutation function such that the prediction is \( \hat{Y} = (y_{b(1)}, ..., y_{b(h)}) \). We use the following two metrics to evaluate the walkthrough planning outputs order:

- Hamming Distance counts the number of \( i \) such that \( i \neq b(i) \).
Table 2: Results for walkthrough planning. Our model trained for procedure planning can also address walkthrough planning. It significantly outperforms the baseline by explicit sequential reasoning of what actions need to be performed first, and is less distracted by the visual appearances.

|   | Uniform | VO | CIGAN [14] | Ours w/o T | Ours w/o P | Ours |
|---|---------|----|------------|------------|------------|------|
|   |         |    |            |            |            |      |
| $h = 4$ Hamming | 1.06 | 1.02 | 0.57 | 0.99 | 0.33 | **0.26** |
|   | Pair Acc. | 46.85% | 49.06% | 71.55% | 50.45% | 83.33% | **86.81%** |
| $h = 5$ Hamming | 1.95 | 1.99 | 1.36 | 2.01 | 1.08 | **0.88** |
|   | Pair Acc. | 52.23% | 50.31% | 68.41% | 47.39% | 77.11% | **81.21%** |

Figure 4: Walkthrough planning qualitative results for changing tires. The steps to sort are ‘get tools out’, ‘loose tires’, and ‘jack up.’ Our model successfully reasons that the tools are needed first for the later steps, while the baselines are more distracted by the visual appearances.

- **Pairwise Accuracy** calculates if the order between a pair $i$ and $j$ is respected by $b(i)$ and $b(j)$. It is given by $\frac{2}{h(h-1)} \sum_{i<j, i \neq j} \{b(i) < b(j)\}$.

**Results.** The results are shown in Table 2. VO is unable to improve much over uniform without modeling the actions. CIGAN [14] is able to learn reasonable models beyond Uniform without using action supervision. However, the complexity of the instructional videos requires explicit modeling of the transition dynamics conditioned on the semantic actions. Our full model learned for procedure planning successfully transfers to walkthrough planning and significantly outperforms all baselines on all metrics. It is interesting to see that Ours w/o $P$ actually outperforms Ours w/o $T$ in this case. Ours w/o $P$ learns the transition dynamics $T$ to directly anticipate the visual effect of an action $a$, which is better suited for walkthrough planning. By just using $P$ the model is more accurate at predicting the actions, but it is not able to retrieve the correct visual observations. Our full model combines the strength of the two through conjugate constraints when learning the transition dynamics and is applicable to both planning and walkthrough planning. The qualitative results are shown in Figure 4 where the person is changing the tire. Our full model is able to plan the correct order for all video clips. The most challenging step is the second step, where the person goes to take the tools, and the video is visually different from the rest of the steps. Neither of the baseline models is able to understand that to perform the rest of the steps, the person needs to get the tools first.

5 Conclusion

We presented a framework for procedure planning in real-world instructional videos. We address the challenge of open-vocabulary state and action spaces by learning plannable representations with conjugate constraints on the latent space. Our experimental results show our framework is able to learn high-level semantic representations that are plannable and significantly outperforms the baselines across different metrics on two challenging tasks: procedure planning and walkthrough planning. In future work, we intend to incorporate object-oriented models to further explore the objects and predicates relations from complex visual dynamics data.
Acknowledgments

This work was partially funded by Toyota Research Institute (TRI). This article solely reflects the opinions and conclusions of its authors and not TRI or any other Toyota entity.

References

[1] Yazan Abu Farha, Alexander Richard, and Juergen Gall. When will you do what?-anticipating temporal occurrences of activities. In CVPR, 2018.

[2] Pulkit Agrawal, Ashvin V Nair, Pieter Abbeel, Jitendra Malik, and Sergey Levine. Learning to poke by poking: Experiential learning of intuitive physics. In NeurIPS, 2016.

[3] Jean-Baptiste Alayrac, Ivan Laptev, Josef Sivic, and Simon Lacoste-Julien. Joint discovery of object states and manipulation actions. In ICCV, 2017.

[4] Chelsea Finn and Sergey Levine. Deep visual foresight for planning robot motion. In ICRA, 2017.

[5] Yanwei Fu and Leonid Sigal. Semi-supervised vocabulary-informed learning. In CVPR, 2016.

[6] Malik Ghallab, Dana Nau, and Paolo Traverso. Automated Planning: theory and practice. Elsevier, 2004.

[7] Sergio Guadarrama, Erik Rodner, Kate Saenko, Ning Zhang, Ryan Farrell, Jeff Donahue, and Trevor Darrell. Open-vocabulary object retrieval. In Robotics: science and systems, volume 2, page 6, 2014.

[8] Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels. In ICML, 2019.

[9] Bradley Hayes and Brian Scassellati. Autonomously constructing hierarchical task networks for planning and human-robot collaboration. In ICRA, 2016.

[10] De-An Huang, Shyamal Buch, Lucio Dery, Animesh Garg, Li Fei-Fei, and Juan Carlos Niebles. Finding “it”: Weakly supervised reference-aware visual grounding in instructional videos. In CVPR, 2018.

[11] De-An Huang, Suraj Nair, Danfei Xu, Yuke Zhu, Animesh Garg, Li Fei-Fei, Silvio Savarese, and Juan Carlos Niebles. Neural task graphs: Generalizing to unseen tasks from a single video demonstration. In CVPR, 2019.

[12] Dinesh Jayaraman, Frederik Ebert, Alexei A Efros, and Sergey Levine. Time-agnostic prediction: Predicting predictable video frames. arXiv preprint arXiv:1808.07784, 2018.

[13] George Konidaris, Leslie Pack Kaelbling, and Tomas Lozano-Perez. From skills to symbols: Learning symbolic representations for abstract high-level planning. Journal of Artificial Intelligence Research, 61: 215–289, 2018.

[14] Thanard Kurutach, Aviv Tamar, Ge Yang, Stuart J Russell, and Pieter Abbeel. Learning plannable representations with causal infogan. In NeurIPS, 2018.

[15] Tian Lan, Tsung-Chuan Chen, and Silvio Savarese. A hierarchical representation for future action prediction. In ECCV, 2014.

[16] MarcAurelio Ranzato, Arthur Szlam, Joan Bruna, Michael Mathieu, Ronan Collobert, and Sumit Chopra. Video (language) modeling: a baseline for generative models of natural videos. arXiv preprint arXiv:1412.6604, 2014.

[17] Nicholas Rhinehart and Kris M Kitani. First-person activity forecasting with online inverse reinforcement learning. In ICCV, 2017.

[18] Pierre Sermanet, Corey Lynch, Yevgen Chebotar, Jasmine Hsu, Eric Jang, Stefan Schaal, Sergey Levine, and Google Brain. Time-contrastive networks: Self-supervised learning from video. In ICRA, 2018.

[19] A Srinivas, A Jabri, P Abbeel, S Levine, and C Finn. Universal planning networks. In ICML, 2018.

[20] Chen Sun, Austin Myers, Carl Vondrick, Kevin Murphy, and Cordelia Schmid. Videobert: A joint model for video and language representation learning. arXiv preprint arXiv:1904.01766, 2019.

[21] Yansong Tang, Dajun Ding, Yongming Rao, Yu Zheng, Danyang Zhang, Lili Zhao, Jiwen Lu, and Jie Zhou. Coin: A large-scale dataset for comprehensive instructional video analysis. arXiv preprint arXiv:1903.02874, 2019.
[22] Carl Vondrick, Hamed Pirsiavash, and Antonio Torralba. Anticipating visual representations from unlabeled video. In CVPR, 2016.

[23] Manuel Watter, Jost Springenberg, Joschka Boedecker, and Martin Riedmiller. Embed to control: A locally linear latent dynamics model for control from raw images. In NeurIPS, 2015.

[24] Kuo-Hao Zeng, William B Shen, De-An Huang, Min Sun, and Juan Carlos Niebles. Visual forecasting by imitating dynamics in natural sequences. In ICCV, 2017.

[25] Hang Zhao, Xavier Puig, Bolei Zhou, Sanja Fidler, and Antonio Torralba. Open vocabulary scene parsing. In ICCV, 2017.

[26] Luowei Zhou, Chenliang Xu, and Jason J Corso. Towards automatic learning of procedures from web instructional videos. In AAAI, 2018.

[27] Dimitri Zhukov, Jean-Baptiste Alayrac, Ramazan Gokberk Cinbis, David Fouhey, Ivan Laptev, and Josef Sivic. Cross-task weakly supervised learning from instructional videos. arXiv preprint arXiv:1903.08225, 2019.