Abstract: Visual model-based reinforcement learning (RL) has the potential to enable sample-efficient robot learning from visual observations. Yet the current approaches typically train a single model end-to-end for learning both visual representations and dynamics, making it difficult to accurately model the interaction between robots and small objects. In this work, we introduce a visual model-based RL framework that decouples visual representation learning and dynamics learning. Specifically, we train an autoencoder with convolutional layers and vision transformers (ViT) to reconstruct pixels given masked convolutional features, and learn a latent dynamics model that operates on the representations from the autoencoder. Moreover, to encode task-relevant information, we introduce an auxiliary reward prediction objective for the autoencoder. We continually update both autoencoder and dynamics model using online samples collected from environment interaction. We demonstrate that our decoupling approach achieves state-of-the-art performance on a variety of visual robotic tasks from Meta-world and RLBench, e.g., we achieve 81.7% success rate on 50 visual robotic manipulation tasks from Meta-world, while the baseline achieves 67.9%. Code is available on the project website: https://sites.google.com/view/mwm-rl.

1 Introduction

Model-based reinforcement learning (RL) holds the promise of sample-efficient robot learning by learning a world model and leveraging it for planning [1, 2, 3] or generating imaginary states for behavior learning [4, 5]. These approaches have also previously been applied to environments with visual observations, by learning an action-conditional video prediction model [6, 7] or a latent dynamics model that predicts compact representations in an abstract latent space [8, 9]. However, learning world models on environments with complex visual observations, e.g., accurately modeling interactions with small objects, is an open challenge.

We argue that this difficulty comes from the design of current approaches that typically optimize the world model end-to-end for learning both visual representations and dynamics [9, 10]. This imposes a trade-off between learning representations and dynamics that can prevent world models from accurately capturing visual details, making it difficult to predict forward into the future. Another approach is to learn representations and dynamics separately, such as earlier work by Ha and Schmidhuber [11] who train a variational autoencoder (VAE) [12] and a dynamics model on top of the VAE features. However, separately-trained VAE representations may not be amenable to dynamics learning [8, 10] or may not capture task-relevant details [11].

On the other hand, masked autoencoders (MAE) [13] have recently been proposed as an effective and scalable approach to visual representation learning, by training a self-supervised vision transformer (ViT) [14] to reconstruct masked patches. While it motivates us to learn world models on top of MAE representations, we find that MAE often struggles to capture fine-grained details within patches. Because capturing visual details, e.g., object positions, is crucial for solving visual control tasks, it is desirable to develop a representation learning method that captures such details but also achieves the benefits of MAE such as stability, compute-efficiency, and scalability.
In this paper, we present Masked World Models (MWM), a visual model-based RL algorithm that decouples visual representation learning and dynamics learning. The key idea of MWM is to train an autoencoder that reconstructs visual observations with convolutional feature masking, and a latent dynamics model on top of the autoencoder. By introducing early convolutional layers and masking out convolutional features instead of pixel patches, our approach enables the world model to capture fine-grained visual details from complex visual observations. Moreover, in order to learn task-relevant information that might not be captured solely by the reconstruction objective, we introduce an auxiliary reward prediction task for the autoencoder. Specifically, we separately update visual representations and dynamics by repeating the iterative processes of (i) training the autoencoder with convolutional feature masking and reward prediction, and (ii) learning the latent dynamics model that predicts visual representations from the autoencoder (see Figure 1).

Contributions We highlight the contributions of our paper below:

• We demonstrate the effectiveness of decoupling visual representation learning and dynamics learning for visual model-based RL. MWM significantly outperforms a state-of-the-art model-based baseline [15] on various visual control tasks from Meta-world [16] and RLBench [17].

• We show that a self-supervised ViT trained to reconstruct visual observations with convolutional feature masking can be effective for visual model-based RL. Interestingly, we find that masking convolutional features can be more effective than pixel patch masking [13], by allowing for capturing fine-grained details within patches. This is in contrast to the observation in Touvron et al. [18], where both perform similarly on the ImageNet classification task [19].

• We show that an auxiliary reward prediction task can significantly improve performance by encoding task-relevant information into visual representations.

2 Related Work

World models from visual observations There have been several approaches to learn visual representations for model-based approaches via image reconstruction [6, 7, 8, 9, 10, 11, 15, 20, 21, 22], e.g., learning a video prediction model [6, 23] or a latent dynamics model [8, 9, 10]. This has been followed by a series of works that demonstrated the effectiveness of model-based approaches for solving video games [15, 24, 22] and visual robot control tasks [7, 21, 25, 26]. There have also been several works that considered different objectives, including bisimulation [27] and contrastive learning [28, 29, 30]. While most prior works optimize a single model to learn both visual representations and dynamics, we instead develop a framework that decouples visual representation learning and dynamics learning.

Self-supervised vision transformers Self-supervised learning with vision transformers (ViT) [14] has been actively studied. For instance, Chen et al. [31] introduced MoCo-v3 which trains a ViT with
We provide more discussion on related works in more detail in Appendix C.

Training self-supervised ViTs with masked image modeling [13, 34, 35, 36, 37, 38, 39] has also been successful. In particular, He et al. [13] proposed a masked autoencoder (MAE) that reconstructs masked pixel patches with an asymmetric encoder-decoder architecture. Unlike MAE, we propose to randomly mask features from early convolutional layers [40] instead of pixel patches and demonstrate that self-supervised ViTs can also be effective for visual model-based RL.

Contrastive learning. Caron et al. [32] introduced DINO which utilizes a self-distillation loss [33], and demonstrated that self-supervised ViTs contain information about the semantic layout of images. Masked autoencoder (MAE) [13] is a self-supervised visual representation technique that trains an autoencoder to reconstruct raw pixels with randomly masked patches consisting of pixels. Following a scheme introduced in vision transformer (ViT) [14], the observation \( o_t \in \mathbb{R}^{H \times W \times C} \) is processed with a patchify stem that reshapes \( o_t \) into a sequence of 2D patches \( h_t \in \mathbb{R}^{N \times (P^2C)} \), where \( P \) is the patch size and \( N = HW/P^2 \) is the number of patches. Then a subset of patches is randomly masked with a ratio of \( m \) to construct \( h_t^m \in \mathbb{R}^{M \times (P^2C)} \).

**Patchify stem:** \( h_t = f_{\phi}^{\text{patch}}(o_t) \)

**Masking:** \( h_t^m \sim p^{\text{mask}}(h_t^m | h_t, m) \)
A ViT encoder embeds only the remaining patches \( h_t^m \) into \( D \)-dimensional vectors, concatenates the embedded tokens with a learnable CLS token, and processes them through a series of Transformer layers [44]. Finally, a ViT decoder reconstructs the observation by processing tokens from the encoder and learnable mask tokens through Transformer layers followed by a linear output head:

\[
\text{ViT encoder: } \quad z_t^m \sim p_\phi(z_t^m \mid h_t^m) \quad \text{ViT decoder: } \quad \hat{\omega}_t \sim p_\phi(\hat{\omega}_t \mid z_t^m)
\]  

(4)

All the components parametrized by \( \phi \) are jointly optimized to minimize the mean squared error (MSE) between the reconstructed and original pixel patches. MAE computes \( z_t^0 \) without masking, and utilizes its first component (i.e., CLS representation) for downstream tasks (e.g., image classification).

4 Masked World Models

In this section, we present Masked World Models (MWM), a visual model-based RL framework for learning accurate world models by separately learning visual representations and environment dynamics. Our method repeats (i) updating an autoencoder with convolutional feature masking and an auxiliary reward prediction task (see Section 4.1), (ii) learning a dynamics model in the latent space of the autoencoder (see Section 4.2), and (iii) collecting samples from environment interaction.

We provide the overview and pseudocode of MWM in Figure 1 and Appendix D, respectively.

4.1 Visual Representation Learning

It has been observed that masked image modeling with a ViT architecture [13, 34, 36] enables compute-efficient and stable self-supervised visual representation learning. This motivates us to adopt this approach for visual model-based RL, but we find that masked image modeling with commonly used pixel patch masking [13] often makes it difficult to learn fine-grained details within patches, e.g., small objects (see Appendix B for a motivating example). While one can consider small-size patches, this would increase computational costs due to the quadratic complexity of self-attention layers.

To handle this issue, we instead propose to train an autoencoder that reconstructs raw pixels given randomly masked convolutional features. Unlike previous approaches that utilize a patchify stem and randomly mask pixel patches (see Section 3), we adopt a convolution stem [14, 40] that processes \( o_t \) through a series of convolutional layers followed by a flatten layer, to obtain \( h_t^c \in \mathbb{R}^{N_c \times D} \) where \( N_c \) is the number of convolutional features. Then \( h_t^c \) is randomly masked with a ratio of \( m \) to obtain \( h_t^{c,m} \in \mathbb{R}^{M_c \times D} \), and ViT encoder and decoder process \( h_t^{c,m} \) to reconstruct raw pixels.

\[
\text{Convolution stem: } \quad h_t^c = f_\phi^{\text{conv}}(o_t) \quad \text{Masking: } \quad h_t^{c,m} \sim \pi_\phi(h_t^{c,m} \mid h_t^c, m) \quad \text{ViT encoder: } \quad \hat{\omega}_t \sim p_\phi(\hat{\omega}_t \mid z_t^{c,m})
\]  

(5)

Because early convolutional layers mix low-level details, we find that our autoencoder can effectively reconstruct all the details within patches by learning to extract information from nearby non-masked features (see Figure 7 for examples). This enables us to learn visual representations capturing such details while also achieving the benefits of MAE, e.g., stability and compute-efficiency\(^3\).

Reward prediction In order to encode task-relevant information that might not be captured solely by the reconstruction objective, we introduce an auxiliary objective for the autoencoder to predict rewards jointly with pixels. Specifically, we make the autoencoder predict the reward \( r_t \) from \( z_t^{c,m} \) in conjunction with raw pixels.

\[
\text{ViT decoder with reward prediction: } \quad \hat{\omega}_t, \hat{r}_t \sim p_\phi(\hat{\omega}_t, \hat{r}_t \mid z_t^{c,m})
\]  

(6)

In practice, we concatenate one additional learnable mask token to inputs of the ViT decoder, and utilize the corresponding output representation for predicting the reward with a linear output head.

High masking ratio Introducing early convolutional layers might impede the masked reconstruction tasks because they propagate information across patches [18], and the model can exploit this to find a shortcut to solve reconstruction tasks. However, we find that a high masking ratio (i.e., 75%) can prevent the model from finding such shortcuts and induce useful representations (see Figure 6(b) for supporting experimental results). This also aligns with the observation from Touvron et al. [18], where masked image modeling [34] with a convolution stem [45] can achieve competitive performance with the patchify stem on the ImageNet classification task [19].

\(^3\)We also note that Xiao et al. [40] showed that introducing early convolutional layers can stabilize the training of ViT models, which can be helpful for RL that requires stability from the beginning of the training.
4.2 Latent Dynamics Learning

Once we learn visual representations, we leverage them for efficiently learning a dynamics model in the latent space of the autoencoder. Specifically, we obtain the frozen representations \( z_t^c,0 \) from the autoencoder, and then train a variant of RSM whose inputs and reconstruction targets are \( z_t^c,0 \) by replacing the representation model and the image decoder in Equation 1 with following components:

\[
\begin{align*}
\text{Representation model:} & \quad s_t \sim q_\theta(s_t | s_{t-1}, a_{t-1}, z_{t-1}^c) \\
\text{Visual representation decoder:} & \quad z_t^c,0 \sim p_\theta(z_t^c,0 | s_t)
\end{align*}
\]

(7)

Because visual representations capture both high- and low-level information in an abstract form, the model can focus more on dynamics learning by reconstructing them instead of raw pixels (see Section 5.5 for relevant discussion). Here, we also note that we utilize all the elements of \( z_t^c,0 \) unlike MAE that only utilizes CLS representation for downstream tasks. We empirically find this enables the model to receive rich learning signals from reconstructing all the representations containing spatial information (see Appendix I for supporting experiments).

Optimization. Given a random batch \( \{(o_j, r_j, a_j)\}_{j=1}^B \), MWM objective is defined as follows:

\[
L_{\text{mwm}}(\phi, \theta) = \frac{1}{B} \sum_{j=1}^B \left( -\ln p_\phi(o_j | z_j^{c,m}) - \ln p_\phi(r_j | z_j^{c,m}) \right)_{\text{visual representation learning}}
\]

\[
-\ln p_\theta(z_{t-1}^c,0 | s_{t-1}) - \ln p_\theta(r_{t-1} | s_{t-1}) + \beta \text{KL} \left[ q_\theta(s_j | s_{j-1}, a_{j-1}, z_{j-1}^{c,0}) \| p_\theta(s_j | s_{j-1}, a_{j-1}) \right]_{\text{dynamics learning}}
\]

(8)

5 Experiments

We evaluate MWM on various robotics benchmarks, including Meta-world [16] (see Section 5.1), RLBench [17] (see Section 5.2), and DeepMind Control Suite [46] (see Section 5.3). We remark that these benchmarks consist of diverse and challenging visual robotic tasks. We also analyze algorithmic design choices in-depth (see Section 5.4) and provide a qualitative analysis of how our decoupling approach works by visualizing the predictions from the latent dynamics model (see Section 5.5).

Implementation. We use visual observations of \( 64 \times 64 \times 3 \). For the convolution stem, we stack 3 convolution layers with the kernel size of 4 and stride 2, followed by a linear projection layer.
We use a 4-layer ViT encoder and a 3-layer ViT decoder. We find that initializing the autoencoder with a warm-up schedule at the beginning of training is helpful. Unlike MAE, we compute the loss on entire pixels because we do not apply masking to pixels. For world models, we build our implementation on top of DreamerV2 [15]. To take a sequence of autoencoder representations as inputs, we replace a CNN encoder and decoder with a 2-layer Transformer encoder and decoder. We use same hyperparameters within the same benchmark. More details are available in Appendix E.

5.1 Meta-world Experiments

Environment details In order to use a single camera viewpoint consistently over all 50 tasks, we use the modified corner2 camera viewpoint for all tasks. In our experiments, we classify 50 tasks into easy, medium, hard, and very hard tasks where experiments are run over 500K, 1M, 2M, 3M environments steps with action repeat of 2, respectively. More details are available in Appendix F.

Results In Figure 3, we report the performance on a set of selected six challenging tasks that require agents to control robot arms to interact with small objects. We find that MWM significantly outperforms DreamerV2 in terms of both sample-efficiency and final performance. In particular, MWM achieves > 80% success rate on Pick Place while DreamerV2 struggles to solve the task. These results show that our approach of separating visual representation learning and dynamics learning can learn accurate world models on challenging domains. We also note that DreamerV2 learns visual representations with the reward prediction loss, which implies that our superior performance does not come from utilizing additional information. Figure 4(a) shows the aggregate performance over all the 50 tasks from the benchmark, demonstrating that our method consistently outperforms DreamerV2 overall. We also provide learning curves on all individual tasks in Appendix G, where MWM consistently achieves similar or better performance on most tasks.

5.2 RLBench Experiments

Environment details In order to evaluate our method on more challenging visual robotic manipulation tasks, we consider RLBench [17], which has previously acted as an effective proxy for real-robot performance [48]. Since RLBench consists of sparse-reward and challenging tasks, solving them typically requires expert demonstrations, specialized network architectures, additional inputs (e.g., point cloud and proprioceptive states), and an action mode that requires path planning [47, 48, 49, 50]. While we could utilize some of these components, we instead leave this as future work in order to maintain a consistent evaluation setup across multiple domains. In our experiments, we instead consider two relatively easy tasks with dense rewards, and utilize an action mode that specifies the delta of joint positions. We provide more details in Appendix F.

Results As shown in Figure 4(b) and Figure 4(c), we observe that our approach can also be effective on RLBench tasks, significantly outperforming DreamerV2. In particular, DreamerV2
achieves < 20% success rate on Reach Target, while our approach can solve the tasks with > 80% success rates. We find that this is because DreamerV2 fails to capture target positions in visual observations, while our method can capture such details (see Section 5.5 for relevant discussion and visualizations). However, we also note that these results are preliminary because they are still too sample-inefficient to be used for real-world scenarios. We provide more discussion in Section 6.

5.3 DeepMind Control Suite Experiments

Environment details In order to demonstrate that our approach is generally applicable to diverse visual control tasks, we also evaluate our method on visual locomotion tasks from the widely used DeepMind Control Suite benchmark. Following a standard setup in Hafner et al. [21], we use an action repeat of 2 and default camera configurations. We provide more details in Appendix F.

Results Figure 5 shows that our method achieves competitive performance to DreamerV2 on visual locomotion tasks (i.e., Quadruped tasks), demonstrating the generality of our approach across diverse visual control tasks. We also observe that our method outperforms DreamerV2 on Reach Duplo, which is one of a few manipulation tasks in the benchmark (see Figure 2(e) for an example). This implies that our method is effective on environments where the model should capture fine-grained details like object positions. More results are available in Appendix H, where trends are similar.

5.4 Ablation Study

Convolutional feature masking We compare convolutional feature masking with pixel masking (i.e., MAE) in Figure 6(a), which shows that convolutional feature masking significantly outperforms pixel masking. Both results are achieved with the reward prediction. This demonstrates that enabling the model to capture fine-grained details within patches can be important for visual control. We also report the performance with varying masking ratio \( m \in \{0.25, 0.5, 0.75, 0.9\} \) in Figure 6(b). As we discussed in Section 4.1, we find that \( m = 0.75 \) achieves better performance than \( m \in \{0.25, 0.5\} \) because strong regularization can prevent the model from finding a shortcut from input pixels. However, we also find that too strong regularization (i.e., \( m = 0.9 \)) degrades the performance.
Reward prediction In Figure 6(c), we find that performance significantly degrades without reward prediction, which shows that the reconstruction objective might not be sufficient for learning task-relevant information. It would be an interesting future direction to develop a representation learning scheme that learns task-relevant information without rewards because they might not be available in practice. We provide more ablation studies and learning curves on individual tasks in Appendix I. Moreover, we also show that reward prediction allows for learning useful representations that can be generally applicable to diverse robotic manipulation tasks in Appendix L.

5.5 Qualitative Analysis

We visually investigate how our world model works compared to the world model of DreamerV2. Specifically, we visualize the future frames predicted by latent dynamics models on Reach Target from RL Bench in Figure 7. In this task, a robot arm should reach a target position specified by a red block in visual observations (see Figure 2(c)), which changes every trial. Thus, it is crucial for the model to accurately predict the position of red blocks for solving the tasks. We find that our world model effectively captures the position of red blocks, while DreamerV2 fails. Interestingly, we also observe that our latent dynamics model ignores the components that are not task-relevant such as blue and orange blocks, though the reconstructions from the autoencoder are capturing all the details. This shows how our decoupling approach works: it encourages the autoencoder to focus on learning representations capturing the details and the dynamics model to focus on modeling task-relevant components of environments. We provide more examples in Appendix B.

6 Discussion

We have presented Masked World Models (MWM), which is a visual model-based RL framework that decouples visual representation learning and dynamics learning. By learning a latent dynamics model operating in the latent space of a self-supervised ViT, we find that our approach allows for solving a variety of visual control tasks from Meta-world, RL Bench, and DeepMind Control Suite.

Limitation Despite the results, there are a number of areas for improvement. As we have shown in Figure 6(c), the performance of our approach heavily depends on the auxiliary reward prediction task. This might be because our autoencoder is not learning temporal information, which is crucial for learning task-relevant information. It would be interesting to investigate the performance of video representation learning with ViTs [36, 51]. It would also be interesting to study introducing auxiliary prediction for other modalities, such as audio. Another weakness is that our model operates only on RGB pixels from a single camera viewpoint; we look forward to a future work that incorporates different input modalities such as proprioceptive states and point clouds, building on top of the recent multi-modal learning approaches [52, 53]. Finally, our approach trains behaviors from scratch, which makes it still too sample-inefficient to be used in real-world scenarios. Leveraging a small number of demonstrations, incorporating the action mode with path planning [47], or pre-training a world model on video datasets [54] are directions we hope to investigate in future works.
Acknowledgments

We would like to thank Jongjin Park and Sihyun Yu for helpful discussions. We also thank Cirrascale Cloud Services\(^4\) for providing compute resources. This work was partially supported by Office of Naval Research under grant N00014-21-1-2769 and grant N00014-22-1-2121, the Darpa RACER program, the Hong Kong Centre for Logistics Robotics, BMW, and Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2019-0-00075, Artificial Intelligence Graduate School Program (KAIST)).

References

[1] K. Chua, R. Calandra, R. McAllister, and S. Levine. Deep reinforcement learning in a handful of trials using probabilistic dynamics models. In Advances in neural information processing systems, 2018.

[2] M. Deisenroth and C. E. Rasmussen. Pilco: A model-based and data-efficient approach to policy search. In International Conference on Machine Learning, 2011.

[3] I. Lenz, R. A. Knepper, and A. Saxena. Deepmpc: Learning deep latent features for model predictive control. In Robotics: Science and Systems, 2015.

[4] T. Kurutach, I. Clavera, Y. Duan, A. Tamar, and P. Abbeel. Model-ensemble trust-region policy optimization. In International Conference on Learning Representations, 2018.

[5] M. Janner, J. Fu, M. Zhang, and S. Levine. When to trust your model: Model-based policy optimization. Advances in Neural Information Processing Systems, 2019.

[6] C. Finn and S. Levine. Deep visual foresight for planning robot motion. In 2017 IEEE International Conference on Robotics and Automation (ICRA), 2017.

[7] F. Ebert, C. Finn, S. Dasari, A. Xie, A. Lee, and S. Levine. Visual foresight: Model-based deep reinforcement learning for vision-based robotic control. arXiv preprint arXiv:1812.00568, 2018.

[8] M. Watter, J. Springenberg, J. Boedecker, and M. Riedmiller. Embed to control: A locally linear latent dynamics model for control from raw images. In Advances in neural information processing systems, 2015.

[9] D. Hafner, T. Lillicrap, I. Fischer, R. Villegas, D. Ha, H. Lee, and J. Davidson. Learning latent dynamics for planning from pixels. In International Conference on Machine Learning, 2019.

[10] M. Zhang, S. Vikram, L. Smith, P. Abbeel, M. Johnson, and S. Levine. Solar: Deep structured representations for model-based reinforcement learning. In International Conference on Machine Learning, 2019.

[11] D. Ha and J. Schmidhuber. World models. In Advances in Neural Information Processing Systems, 2018.

[12] D. P. Kingma and M. Welling. Auto-encoding variational bayes. In International Conference on Learning Representations, 2014.

[13] K. He, X. Chen, S. Xie, Y. Li, P. Dollár, and R. Girshick. Masked autoencoders are scalable vision learners. arXiv preprint arXiv:2111.06377, 2021.

[14] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In International Conference on Learning Representations, 2021.

[15] D. Hafner, T. Lillicrap, M. Norouzi, and J. Ba. Mastering atari with discrete world models. In International Conference on Learning Representations, 2021.

\(^4\)https://cirrascale.com
[16] T. Yu, D. Quillen, Z. He, R. Julian, K. Hausman, C. Finn, and S. Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In Conference on Robot Learning, 2020.

[17] S. James, Z. Ma, D. R. Arrojo, and A. J. Davison. RLBench: The robot learning benchmark & learning environment. IEEE Robotics and Automation Letters, 2020.

[18] H. Touvron, M. Cord, A. El-Nouby, J. Verbeek, and H. Jégou. Three things everyone should know about vision transformers. arXiv preprint arXiv:2203.09795, 2022.

[19] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, 2009.

[20] C. Finn, X. Y. Tan, Y. Duan, T. Darrell, S. Levine, and P. Abbeel. Deep spatial autoencoders for visuomotor learning. In 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016.

[21] D. Hafner, T. Lillicrap, J. Ba, and M. Norouzi. Dream to control: Learning behaviors by latent imagination. In International Conference on Learning Representations, 2020.

[22] L. Kaiser, M. Babaeizadeh, P. Milos, B. Osinski, R. H. Campbell, K. Czechowski, D. Erhan, C. Finn, P. Kozakowski, S. Levine, et al. Model-based reinforcement learning for atari. In International Conference on Learning Representations, 2019.

[23] A. Gupta, S. Tian, Y. Zhang, J. Wu, R. Martín-Martín, and L. Fei-Fei. Maskvit: Masked visual pre-training for video prediction. arXiv preprint arXiv:2206.11894, 2022.

[24] W. Ye, S. Liu, T. Kurutach, P. Abbeel, and Y. Gao. Mastering atari games with limited data. Advances in Neural Information Processing Systems, 2021.

[25] T. Seyde, W. Schwarting, S. Karaman, and D. Rus. Learning to plan optimistically: Uncertainty-guided deep exploration via latent model ensembles. In Conference on Robot Learning, 2021.

[26] O. Rybkin, C. Zhu, A. Nagabandi, K. Daniilidis, I. Mordatch, and S. Levine. Model-based reinforcement learning via latent-space collocation. In International Conference on Machine Learning, 2021.

[27] C. Gelada, S. Kumar, J. Buckman, O. Nachum, and M. G. Bellemare. Deepmdp: Learning continuous latent space models for representation learning. In International Conference on Machine Learning, 2019.

[28] T. D. Nguyen, R. Shu, T. Pham, H. Bui, and S. Ermon. Temporal predictive coding for model-based planning in latent space. In International Conference on Machine Learning, 2021.

[29] M. Okada and T. Taniguchi. Dreaming: Model-based reinforcement learning by latent imagination without reconstruction. In 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021.

[30] F. Deng, I. Jang, and S. Ahn. Dreamerpro: Reconstruction-free model-based reinforcement learning with prototypical representations. arXiv preprint arXiv:2110.14565, 2021.

[31] X. Chen, S. Xie, and K. He. An empirical study of training self-supervised vision transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[32] M. Caron, H. Touvron, I. Misra, H. Jégou, J. Mairal, P. Bojanowski, and A. Joulin. Emerging properties in self-supervised vision transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[33] G. Hinton, O. Vinyals, J. Dean, et al. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

[34] H. Bao, L. Dong, and F. Wei. Beit: Bert pre-training of image transformers. arXiv preprint arXiv:2106.08254, 2021.
[35] Z. Li, Z. Chen, F. Yang, W. Li, Y. Zhu, C. Zhao, R. Deng, L. Wu, R. Zhao, M. Tang, et al. Mst: Masked self-supervised transformer for visual representation. In Advances in Neural Information Processing Systems, 2021.

[36] C. Feichtenhofer, H. Fan, Y. Li, and K. He. Masked autoencoders as spatiotemporal learners. arXiv preprint arXiv:2205.09113, 2022.

[37] Z. Xie, Z. Zhang, Y. Cao, Y. Lin, J. Bao, Z. Yao, Q. Dai, and H. Hu. Simmim: A simple framework for masked image modeling. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022.

[38] C. Wei, H. Fan, S. Xie, C.-Y. Wu, A. Yuille, and C. Feichtenhofer. Masked feature prediction for self-supervised visual pre-training. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022.

[39] J. Zhou, C. Wei, H. Wang, W. Shen, C. Xie, A. Yuille, and T. Kong. ibot: Image bert pre-training with online tokenizer. arXiv preprint arXiv:2111.07832, 2021.

[40] T. Xiao, M. Singh, E. Mintun, T. Darrell, P. Dollár, and R. Girshick. Early convolutions help transformers see better. In Advances in Neural Information Processing Systems, 2021.

[41] Y. Tassa, S. Tunyasuvunakool, A. Muldal, Y. Doron, S. Liu, S. Bohez, J. Merel, T. Erez, T. Lillicrap, and N. Heess. dm_control: Software and tasks for continuous control. arXiv preprint arXiv:2006.12983, 2020.

[42] R. S. Sutton and A. G. Barto. Reinforcement learning: An introduction. MIT Press, 2018.

[43] A. Alemi, B. Poole, I. Fischer, J. Dillon, R. A. Saurous, and K. Murphy. Fixing a broken elbo. In International Conference on Machine Learning, 2018.

[44] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. Attention is all you need. In Advances in Neural Information Processing Systems, 2017.

[45] B. Graham, A. El-Nouby, H. Touvron, P. Stock, A. Joulin, H. Jégou, and M. Douze. Levit: a vision transformer in convnet’s clothing for faster inference. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[46] Y. Tassa, T. Erez, and E. Todorov. Synthesis and stabilization of complex behaviors through online trajectory optimization. In International Conference on Intelligent Robots and Systems, 2012.

[47] S. James and A. J. Davison. Q-attention: Enabling efficient learning for vision-based robotic manipulation. IEEE Robotics and Automation Letters, 2022.

[48] S. James, K. Wada, T. Laidlow, and A. J. Davison. Coarse-to-Fine Q-attention: Efficient learning for visual robotic manipulation via discretisation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022.

[49] S. James and P. Abbeel. Coarse-to-Fine Q-attention with Learned Path Ranking. arXiv preprint arXiv:2204.01571, 2022.

[50] S. James and P. Abbeel. Coarse-to-Fine Q-attention with Tree Expansion. arXiv preprint arXiv:2204.12471, 2022.

[51] A. Arnab, M. Dehghani, G. Heigold, C. Sun, M. Lučić, and C. Schmid. Vivit: A video vision transformer. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[52] X. Geng, H. Liu, L. Lee, D. Schuurams, S. Levine, and P. Abbeel. Multimodal masked autoencoders learn transferable representations. arXiv preprint arXiv:2205.14204, 2022.

[53] R. Bachmann, D. Mizrahi, A. Atanov, and A. Zamir. Multimae: Multi-modal multi-task masked autoencoders. arXiv preprint arXiv:2204.01678, 2022.
[54] Y. Seo, K. Lee, S. James, and P. Abbeel. Reinforcement learning with action-free pre-training from videos. In International Conference on Machine Learning, 2022.

[55] J. Schulman, P. Moritz, S. Levine, M. Jordan, and P. Abbeel. High-dimensional continuous control using generalized advantage estimation. arXiv preprint arXiv:1506.02438, 2015.

[56] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2016.

[57] H. Wu, B. Xiao, N. Codella, M. Liu, X. Dai, L. Yuan, and L. Zhang. Cvt: Introducing convolutions to vision transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021.

[58] J. Dai, K. He, and J. Sun. Convolutional feature masking for joint object and stuff segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3992–4000, 2015.

[59] J. Tompson, R. Goroshin, A. Jain, Y. LeCun, and C. Bregler. Efficient object localization using convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2015.

[60] G. Ghiasi, T.-Y. Lin, and Q. V. Le. Dropblock: A regularization method for convolutional networks. Advances in neural information processing systems, 31, 2018.

[61] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 2014.

[62] J. Park, Y. Seo, C. Liu, L. Zhao, T. Qin, J. Shin, and T.-Y. Liu. Object-aware regularization for addressing causal confusion in imitation learning. In Advances in Neural Information Processing Systems, 2021.

[63] A. Van Den Oord, O. Vinyals, et al. Neural discrete representation learning. In Advances in Neural Information Processing Systems, 2017.

[64] M. Jaderberg, V. Mnih, W. M. Czarnecki, T. Schaul, J. Z. Leibo, D. Silver, and K. Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. In International Conference on Learning Representations, 2017.

[65] M. Schwarzer, A. Anand, R. Goel, R. D. Hjelm, A. Courville, and P. Bachman. Data-efficient reinforcement learning with self-predictive representations. In International Conference on Learning Representations, 2021.

[66] T. Yu, C. Lan, W. Zeng, M. Feng, Z. Zhang, and Z. Chen. Playvirtual: Augmenting cycle-consistent virtual trajectories for reinforcement learning. In Advances in Neural Information Processing Systems, 2021.

[67] T. Yu, Z. Zhang, C. Lan, Z. Chen, and Y. Lu. Mask-based latent reconstruction for reinforcement learning. arXiv preprint arXiv:2201.12096, 2022.

[68] P. S. Castro. Scalable methods for computing state similarity in deterministic markov decision processes. In Proceedings of the AAAI Conference on Artificial Intelligence, 2020.

[69] A. Zhang, R. McAllister, R. Calandra, Y. Gal, and S. Levine. Learning invariant representations for reinforcement learning without reconstruction. In International Conference on Learning Representations, 2021.

[70] A. v. d. Oord, Y. Li, and O. Vinyals. Representation learning with contrastive predictive coding. In Advances in Neural Information Processing Systems, 2018.

[71] A. Anand, E. Racah, S. Ozair, Y. Bengio, M.-A. Côté, and R. D. Hjelm. Unsupervised state representation learning in atari. In Advances in Neural Information Processing Systems, 2019.

[72] B. Mazoure, R. T. d. Combes, T. Doan, P. Bachman, and R. D. Hjelm. Deep reinforcement and infomax learning. In Advances in Neural Information Processing Systems, 2020.
[73] A. Srinivas, M. Laskin, and P. Abbeel. Curl: Contrastive unsupervised representations for reinforcement learning. In *International Conference on Machine Learning*, 2020.

[74] H. Liu and P. Abbeel. Behavior from the void: Unsupervised active pre-training. *arXiv preprint arXiv:2103.04551*, 2021.

[75] D. Yarats, R. Fergus, A. Lazaric, and L. Pinto. Reinforcement learning with prototypical representations. In *International Conference on Machine Learning*, 2021.

[76] S. Nair, A. Rajeswaran, V. Kumar, C. Finn, and A. Gupta. R3m: A universal visual representation for robot manipulation. *arXiv preprint arXiv:2203.12601*, 2022.

[77] S. Parisi, A. Rajeswaran, S. Purushwalkam, and A. Gupta. The unsurprising effectiveness of pre-trained vision models for control. *arXiv preprint arXiv:2203.03580*, 2022.

[78] M. Minderer, C. Sun, R. Villegas, F. Cole, K. P. Murphy, and H. Lee. Unsupervised learning of object structure and dynamics from videos. In *Advances in Neural Information Processing Systems*, 2019.

[79] L. Manuelli, Y. Li, P. Florence, and R. Tedrake. Keypoints into the future: Self-supervised correspondence in model-based reinforcement learning. *arXiv preprint arXiv:2009.05085*, 2020.

[80] M. Lambeta, P.-W. Chou, S. Tian, B. Yang, B. Maloon, V. R. Most, D. Stroud, R. Santos, A. Byagowi, G. Kammerer, et al. Digit: A novel design for a low-cost compact high-resolution tactile sensor with application to in-hand manipulation. *IEEE Robotics and Automation Letters*, 2020.

[81] N. Das, S. Bechtle, T. Davchev, D. Jayaraman, A. Rai, and F. Meier. Model-based inverse reinforcement learning from visual demonstrations. In *Conference on Robot Learning*, 2021.

[82] D. Yarats, A. Zhang, I. Kostrikov, B. Amos, J. Pineau, and R. Fergus. Improving sample efficiency in model-free reinforcement learning from images. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2021.

[83] E. Shelhamer, P. Mahmoudieh, M. Argus, and T. Darrell. Loss is its own reward: Self-supervision for reinforcement learning. *arXiv preprint arXiv:1612.07307*, 2016.

[84] D. Yarats, R. Fergus, A. Lazaric, and L. Pinto. Mastering visual continuous control: Improved data-augmented reinforcement learning. *arXiv preprint arXiv:2107.09645*, 2021.

[85] M. Laskin, K. Lee, A. Stooke, L. Pinto, P. Abbeel, and A. Srinivas. Reinforcement learning with augmented data. In *Advances in Neural Information Processing Systems*, 2020.

[86] I. Kostrikov, D. Yarats, and R. Fergus. Image augmentation is all you need: Regularizing deep reinforcement learning from pixels. In *International Conference on Learning Representations*, 2021.

[87] T. Xiao, I. Radosavovic, T. Darrell, and J. Malik. Masked visual pre-training for motor control. *arXiv preprint arXiv:2203.06173*, 2022.