LOPR: Latent Occupancy PRediction using Generative Models

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Abstract: Environment prediction frameworks are integral for autonomous vehicles, enabling safe navigation in dynamic environments. LiDAR generated occupancy grid maps (L-OGMs) offer a robust bird’s eye-view scene representation that facilitates joint scene predictions without relying on manual labeling unlike commonly used trajectory prediction frameworks. Prior approaches have optimized deterministic L-OGM prediction architectures directly in grid cell space. While these methods have achieved some degree of success in prediction, they occasionally grapple with unrealistic and incorrect predictions. We claim that the quality and realism of the forecasted occupancy grids can be enhanced with the use of generative models. We propose a framework that decouples occupancy prediction into: representation learning and stochastic prediction within the learned latent space. Our approach allows for conditioning the model on other available sensor modalities such as RGB-cameras and high definition maps. We demonstrate that our approach achieves state-of-the-art performance and is readily transferable between different robotic platforms on the real-world NuScenes, Waymo Open, and a custom dataset we collected on an experimental vehicle platform.

Keywords: Occupancy Prediction, Autonomous Driving, Generative Models

1 Introduction

Accurate environment prediction algorithms are essential for autonomous vehicle (AV) navigation in urban settings. Experienced drivers understand scene semantics and recognize the intents of other agents to anticipate their trajectories and safely navigate to their destination. To replicate this process in AVs and other robotic platforms, many environment prediction approaches have been proposed, employing different environment representations and modeling assumptions [1–9].

The modern AV stack comprises several sequential modules trained independently on labeled data. For environment reasoning, object-based prediction algorithms are commonly used [4, 6, 7, 10], which rely on perception systems to create a vectorized representation of the scene with pre-defined agents and environmental features. However, this approach has multiple limitations. 1) It generates marginalized future trajectories for individual agents, rather than a holistic scene prediction which complicates the integration with planning modules [11]. 2) Their reliance on labeled data, sourced either manually or from off-board perception systems [12, 13], diverges from on-board noisy detections. 3) They do not take any sensor measurements into account and depend solely on object detection algorithms which can fail in suboptimal conditions [14, 15]. These approaches also exclude social and topological cues that humans naturally perceive, emphasizing the importance of end-to-end perception-prediction learning [16]. The current drawbacks render the AV stack susceptible to cascading failures, and can lead to poor generalization to unforeseen scenarios. These limitations underscore the need for alternative end-to-end, self-supervised environment modeling approaches.
Given these challenges, occupancy grid maps generated from LiDAR measurements (L-OGMs) have gained popularity as a form of scene representation for prediction. This popularity is due to their minimal data preprocessing requirements, eliminating the need for manual labeling, ability to model the joint prediction of the scene with an arbitrary number of agents (including interactions between agents), and robustness to partial observability and detection failures [1–3, 17]. In addition, the sole requirement for their deployment is a LiDAR sensor, simplifying transfer between different platforms. Our focus is on end-to-end ego-centric L-OGM prediction generated using uncertainty-aware occupancy state estimation approaches [18]. Due to its generality and ability to scale with unlabeled data, we hypothesize that such an L-OGM prediction framework could also serve as a pre-training objective, i.e. a foundational mode, for supervised tasks such as trajectory prediction.

The task of OGM prediction is typically approached similarly to video prediction, by framing the problem as self-supervised sequence-to-sequence learning. In this approach, a scenario is dissected into a history sequence and a target prediction sequence. ConvLSTM-based architectures [19] have been used in previous work for this task due to their ability to handle the spatiotemporal representation of inputs and outputs [1–3, 20, 21]. These approaches are optimized end-to-end in grid cell space, do not account for the stochasticity present in the scene, and neglect other available sensor modalities, e.g. RGB cameras and high definition (HD) maps. As a result, they suffer from blurry predictions, especially at longer time horizons. We propose a prediction framework that reasons over potential futures in the latent space of a generative architecture conditioned on other available sensor modalities, like RGB cameras and maps.

Existing object-based methods use a vectorized representation to predict trajectories [5, 6, 22] or vectorized OGMs (V-OGMs) [8], overlooking important perceptual cues in their predictions. Prior L-OGM-based works [1, 3, 25] do not use available sensor modalities, and consider only deterministic predictions. Our framework addresses these weaknesses in the following contributions:

- We introduce a framework named Latent Occupancy PRediction (LOPR), which performs stochastic L-OGM prediction in the latent space of a generative architecture conditioned on other available sensor modalities, like RGB cameras and maps.
• Through experiments on NuScenes [39] and the Waymo Open Dataset [40], we show that LOPR outperforms SOTA OGM prediction methods qualitatively and quantitatively.
• We demonstrate that LOPR can be conveniently transferred between different robotic platforms by additionally evaluating our framework on a custom robotic dataset.

2 Related Work

OGM Prediction: The majority of prior work in OGM prediction generates OGMs with LiDAR measurements (L-OGMs) and uses an adaptation on the recurrent neural network (RNN) with convolutions. Dequaire et al. [41] applied a Deep Tracking approach [42] to track objects through occlusions and predict future binary OGMs with an RNN and a spatial transformer [43]. Schreiber et al. [20] provided dynamic occupancy grid maps (DOGMas) with cell-wise velocity estimates as input to a ConvLSTM [19] for environment prediction from a stationary platform. Schreiber et al. [21] extended this work to forecast DOGMas in a moving ego-vehicle setting. Mohajerin and Rohani [17] applied a difference learning approach to predict OGMs as seen from the coordinate frame of the first observed time step. Itkina et al. [1] used the PredNet ConvLSTM architecture [44] to achieve ego-centric OGM prediction. Lange et al. [3] reduced the blurring and the gradual disappearance of dynamic obstacles in the predicted grids by developing an attention augmented ConvLSTM mechanism. Concurrently, Toyungyernsub et al. [2] addressed obstacle disappearance with a double-prong framework assuming knowledge of the static and dynamic obstacles. Predicted OGMs often lack agent identity information. Mahjourian et al. [8] addressed this by exploiting occupancy flow estimates to trace back the agent identities from the observed OGM frames. They used upstream perception detections to generate OGMs with vectorized representations (V-OGMs) and hence require manual labeling. Unlike prior work, we perform stochastic OGM predictions in the latent space of generative models of all available sensors without any manual labeling.

Representation Learning in Robotics: The objective of representation learning is to identify a low-dimensional and disentangled representation that makes it easier to achieve the desired performance on a task. Many robotics applications are inspired by the seminal papers on the autoencoder (AE) [45–47], the variational autoencoder (VAE) [29], and the generative adversarial network (GAN) [27]. Ha and Schmidhuber [32] proposed a World Model, where they used a VAE to compress observations and maximize the expected cumulative reward. Kim et al. [38] applied the World Model to neural network simulation for autonomous driving, where they merged the VAE [29] and StyleGAN [28] to increase fidelity of the generated scenes. Similarly, latent spaces have been used in a plethora of other planning and control approaches to learn latent dynamics from pixels [36, 37, 48–50], generate fully imagined trajectories [51], model multi-agent interactions [33], learn competitive policies through self-play [34], imagine goals in goal-conditioned policies [52, 53], and perform meta- and offline reinforcement learning [54, 55]. Diffusion-based generative models [56–59] are increasingly gaining traction due to their high sampling quality. However, their computationally intensive sampling process poses a significant obstacle for real-time robotic applications in the context of perceptual generation. In video prediction tasks, variational and adversarial components have been incorporated into the architecture to capture data stochasticity [60] and improve the realism of the forecasted frames [61], respectively. Since then, large-scale architectures (over 300 million parameters) [62, 63] have been developed for general video prediction, which are not real-time capable on robot hardware. We present the first method, to our knowledge, that performs stochastic L-OGM prediction with transformers entirely in the latent space of a generative model while remaining real-time feasible and parameter efficient (less than 4 million parameters).

3 LOPR: Latent Occupancy PRediction

We propose the Latent Occupancy PRediction (LOPR) model, a framework designed to generate stochastic scene predictions in the form of OGMs. The model uses representations provided by sensor modalities, such as LiDAR-generated OGMs, RGB cameras, and maps. It does not require any manually labeled data and can be deployed on any robot equipped with at least a LiDAR sen-
Figure 2: The illustration shows the LOPR framework which consists of (1) representation learning and (2) stochastic sequence prediction. In the representation learning stage, we train an encoder and decoder in an unsupervised manner. In the sequence prediction stage, we convert our OGM dataset to the low-dimensional representation, and perform training entirely in the latent space of our pre-trained generative model.

3.1 Representation Learning

In the first stage of training, we acquire a pre-trained latent space of all input modalities by training an encoder $E$ and a decoder $D$. Given the input modality $x \in \mathbb{R}^{C \times W \times H}$, the encoder outputs a low-dimensional latent vector $z \in \mathbb{R}^{c \times h \times w}$, and the decoder maps the latent vector to a reconstruction $\hat{x} \in \mathbb{R}^{C \times W \times H}$. The framework is trained using a combination of perceptual loss [65], Kullback-Leibler (KL) regularization [29], patch-based adversarial losses [66] and path regularization [28]:

$$L_{VAEGAN} = \min_{E, D} \max_{\psi} (L_{LPIPS}(x, D(E(x))) - \gamma L_{adv}(D(E(x))) + \beta L_{KL}(x; E, D) + L_{reg}).$$

We employ the adversarial loss to increase the visual fidelity of the generated samples, KL regularization to encourage the posterior $q(z \mid x)$ to be clustered close the prior $p(z) = \mathcal{N}(0, I)$.

3.2 Stochastic Sequence Prediction

Given the pre-trained latent space of our sensor data, we train a stochastic sequence prediction network that receives a history of observations and outputs a distribution of potential future scenarios $p_\theta(z_P \mid z_0 : P)$, where $z_0 : P$ represents compressed observations over $P$ timesteps, $T$ signifies the total sequence length, and $\theta$ are the network weights. To simplify notation, we assume an abuse of notation in that when $z_t$ corresponds to an observation, it includes all sensor modalities; conversely, when referring to the future, it includes only the OGM representation. The environment prediction task is inherently multimodal, and the latent vectors contributing to this stochasticity are unobservable. Drawing from prior work on video prediction [60], we introduce a latent vector $z_{stoch} \sim p(z_{stoch})$ to encapsulate this stochasticity and extend our model to $p_\theta(z_P \mid z_0 : P, z_{stoch})$. During training, we extract the true posterior $p(z_{stoch} \mid z_0 : T)$ using an inference network $z_{stoch} \sim q_\phi(z_{stoch} \mid z_0 : T)$, while at test time, we sample from a pre-defined prior $p(z_{stoch})$. The framework
is optimized using the variational lower bound \([29]\):

\[
\mathcal{L}(z) = -E_{q_\phi(z_{\text{stoch}} \mid z_0:T)} \left[ \log p_\theta(z_{P:T} \mid z_0; p, z_{\text{stoch}}) \right] + D_{KL}(q_\phi(z_{\text{stoch}} \mid z_0:T) \parallel p(z_{\text{stoch}})),
\]

where \(D_{KL}\) is the Kullback-Leibler divergence, and \(p(z_{\text{stoch}})\) is standard Gaussian \([60, 61, 67, 68]\).

We implement our model using a transformer-based architecture, comprised of a scene encoder \(P_{\text{encoder}}; \theta\), an inference network \(Q_\phi\), and an autoregressive decoder \(P_{\text{decoder}}; \theta\). In all transformation-based operations, positional information is provided through a sinusoidal positional encoding \([64]\). To reduce the number of parameters required in the attention layer for processing each token and to facilitate spatial attention, each latent vector \(z \in \mathbb{R}^{c \times h \times w}\) is reshaped along the spatial dimensions to a sequence of smaller cuboids \(z \in \mathbb{R}^{k^2c \times \frac{h}{k} \times \frac{w}{k}}\). This is followed by spatial partitioning. A single latent vector \(z\) thus generates a sequence of \(\frac{hw}{k^2}\) tokens, each of length \(k^2c\).

The scene encoder and inference network are implemented using a transformer architecture, wherein each token can attend to every other token. The scene encoder takes in tokens generated with latent vectors for all sensor modalities and outputs scene contexts \(\text{scene} \text{emb} \in \mathbb{R}^{kc^2}\). The posterior network takes in the all OGM latent vectors, including the future ones, and outputs parameters for the Gaussian distribution \(\mu\) and \(\sigma\), used for \(z_{\text{stoch}}\):

\[
\text{scene} \text{emb} = P_{\text{encoder}}; \theta(z_0; p)
\]

\[
z_{\text{stoch}} \sim \mathcal{N}(\mu_\phi(z_0; T), \sigma_\phi(z_0; T)).
\]

Both \(\text{scene} \text{emb}\) and \(z_{\text{stoch}}\) are concatenated along the temporal dimension and serve as memory tokens to \(P_{\text{decoder}}; \theta\), which is implemented using a causal transformer to generate predictions:

\[
z_t = P_{\text{decoder}}; \theta(z_{0:t-1}, \text{mem} = [\text{scene} \text{emb}, z_{\text{stoch}}])
\]

In the final step, the predicted compressed representations are concatenated, reshaped back to their original dimensions, and then fed into the pretrained decoder \(D\) to produce the OGM predictions.

## 4 Experiments

We analyze our proposed framework based on its pre-trained latent space and how well it performs on environment prediction tasks. We also consider how additional sensor modalities affect the prediction quality. Our framework is tested against prior methods in L-OGM forecasting and top-performing sequence-to-sequence video prediction models of similar scale. We use the open-source datasets, NuScenes \([39]\) and the Waymo Open Dataset \([40]\), for training and evaluation. To demonstrate the versatility of our framework, we evaluate our models on a custom urban robotic dataset. Our results show that LOPR reaches SOTA performance in the prediction task. Our code with additional visualizations is available here.

### 4.1 Datasets

**NuScenes Dataset** \([39]\) is an AV dataset collected in Boston and Singapore. The autonomous vehicle sensor suite includes 6 12Hz RGB cameras, a 20Hz 32-beam LiDAR, GPS, and an IMU. It also provides rasterized maps featuring drivable areas, stop signs, and pedestrian crossings.

**Waymo Open Dataset** is an AV dataset compiled in San Francisco, Phoenix, and Mountain View. The data collection platform incorporates 5 LiDARs, 5 RGB cameras, GPS, and an IMU, with samples collected at 10 Hz. Maps are provided in vectorized form.

**Custom Robot Platform Dataset**: To demonstrate the transferability of our framework, we collect a small dataset comprising 20 scenes, each 20 seconds long, in an urban setting with a mobile robotic platform equipped with Velodyne’s HDL-32E 32-beam LiDAR. Within this dataset, we observe interactions with cars, buses, cyclists, and pedestrians.
**Data Representation:** We generate OGMs using a ground-segmented LiDAR point cloud. The OGM dimensions are $H \times W = 128 \times 128$ with a 0.3 m resolution, corresponding to a 42.7 m $\times$ 42.7 m grid. We downscale RGB images and maps to the same resolution. During the sequence prediction training phase, we provide 5 past OGMs (0.5 s) as observations alongside other sensor modalities, and predict for 15 frames (1.5 s) into the future at 10 Hz. For all open-source datasets, we adhere to the original dataset specification for the train-validation-test split.

**4.2 Architecture and Training Details**

**Architectures:** Our encoder and decoder employ a convolutional network with residual connections, and a latent vector $z \in \mathbb{R}^{64 \times 4 \times 4}$. The discriminator is multi-scale and multi-patch, following previous work [66, 69, 70]. We use a vanilla Transformer implementation provided in PyTorch [71].

**Model Training:** We trained the models using PyTorch Lightning 1.4.2 [71, 72]. We used the AdamW optimizer [73] with a learning rate of $4 \times 10^{-4}$. For representation learning, we used four NVIDIA V100 32 GB GPUs. The autoencoders were trained for 80k steps with a batch size of 128. We trained all prediction models on a Nvidia Titan RTX 24 GB GPU with 256 batch size.

**4.3 Evaluation**

**Baselines:** We benchmark against methods commonly used in L-OGM prediction, such as PredNet [1, 44] and TAAConvLSTM [3]. Due to their representational similarity to our approach, we also draw comparisons with available SOTA video prediction methods of similar scale like SimVP V2 [74], PredRNN V2 [75], and E3DLSTM [76]. We also introduce a baseline that uses the last observed frame as a prediction to assess how effectively the models capture the scene’s motion.

**Quantitative Evaluation:** We evaluate all models using the Image Similarity (IS) metric [77] across the 1.5 s and 3.0 s prediction and the accuracy of occupied cells at the end of the 3.0 s rollout. For stochastic predictions, we sample 10 predictions and evaluate the best-performing one. Similar to the mean squared error (MSE) used in trajectory prediction, we are interested in the relative distance errors between observed objects and predicted position of the object but in the discretized space. The IS metric captures the variations in predicted multi-future agent positions [3]. Commonly used precision-focused metrics, like MSE, penalize a missing moving agent significantly less than a predicted agent’s slight positional shift when compared with the ground truth [3]. The IS metric calculates the smallest Manhattan distance between two grid cells with the same thresholded occupancy. Its numerical evaluation is proportional to the discrepancy between predicted and observed positions and is notably high when an agent completely disappears. We also provide an accuracy of occupied cells at the end of the 3.0 s rollout to highlight the critical issue of vanishing moving objects, a common and prohibitive failure for safety-critical applications.

**5 Results**

**5.1 Latent Space Analysis**

The latent space trained in the representation learning stage is essential to facilitate accurate predictions. If an agent in the observed frames is lost during the encoding phase, the prediction network will have difficulties recovering this information, potentially leading to incorrect forecasting. We investigate the reconstruction performance qualitatively and quantitatively. Our framework successfully recovers each sensor modality’s observation from their respective low-dimensional representations as visualized in Fig. 3. We investigate the impact of KL regularization in Table 1. We observe that high KL regularization is needed for the L-OGM’s VAE-GAN to generate high quality predictions. The KL term induces better regularization and smoothness in the learned latent space, resulting in improved generalization. We hypothesize that predictions in the latent space will unavoidably incur some inaccuracies, and thus, will not perfectly correspond to the ground truth L-OGM data distribution. This better generalization is important when making predictions in the
latent space. We also report the reconstruction performance of camera and map observations. We did not observe significant impact of their regularization on the prediction task.

5.2 Prediction Task

We assess the predictive capabilities of LOPR in Table 2 and show its predictions in Figs. 4 and 5. We investigate the influence of stochasticity and the addition of other sensor modalities by evaluating deterministic and stochastic models conditioned only on L-OGMs, and another stochastic model conditioned on all available inputs. All LOPR variations notably outperform prior work in L-OGM prediction, as evidenced by the IS and accuracy metrics. The improvements become more pronounced with the integration of additional modalities and stochastic modeling. LOPR is also the only framework that markedly outperforms the simple baseline, which repeats the last observation, demonstrating its ability to capture the scene’s dynamics.

In Fig. 4, we visualize the predictions rolled out for 3.0 s into the future, i.e. beyond the prediction horizon used during training. LOPR produces high-quality, realistic predicted frames, supporting quantitative results. Dynamic objects are realistically propagated in the scene and the details of the static environment are maintained, unlike prior approaches [1, 3]. Fig. 5 presents varied prediction samples from challenging scenarios characterized by partial observability. Each sample captures a realistic plausible future rollout. Our framework is capable of inferring a previously unobserved agent entering the L-OGM. Our framework is the first, to the best of our knowledge, to successfully generate realistic stochastic OGM predictions conditioned on multi-modal sensor data.

Prior work that uses ConvLSTM-based architectures optimized for the spatiotemporal prediction task in grid cell space [1–3, 20] suffers from lack of sharpness and poor realism in their predictions. For example, occluded cells are often not preceded by occupied cells, making the frames physically incorrect, and forecasted L-OGMs gradually lose important details over the prediction horizon. Lack of sharpness eventually leads to the vanishing of moving objects and, hence, missing agents in the predictions [1, 3] and a low IS metric value. These failures are not present in LOPR’s predictions.

We also demonstrate successful transfer of our LOPR model trained on the NuScenes dataset to our custom robotic dataset in Table 2 and Fig. 4. The quantitative prediction performance on this dataset is comparable in magnitude to the other datasets, despite the data distribution shift. Thus, LOPR is able to successfully generalize beyond its training data distribution.

6 Limitations

Although decoupling the representation learning and prediction stages allows us to achieve high-quality OGM predictions empirically, LOPR relies on a well trained latent space that may not be tuned for prediction. If the latent encoding misses important scene information (such as moving agents), the prediction network will not be able to recover this information and fail to predict the agent. Furthermore, as any learned module in a safety-critical engineering system, like an AV, LOPR

Table 1: Impact of KL regularization during representation learning on LOPR’s performance in terms of reconstruction and a simplified prediction task using the NuScenes dataset. For all metrics, lower is better.

| KL      | OGM Recon. (IS) | OGM Prediction (IS) | Camera Recon. (MSE) | Map Recon. (MSE) |
|---------|-----------------|---------------------|---------------------|------------------|
| $1 \times 10^{-6}$ | 3.51 ± 0.01 | 14.85 ± 0.72 | 2.21 ± 0.04 | 0.49 ± 0.04 |
| 1.0     | 1.71 ± 0.01     | 15.90 ± 0.34 | 2.89 ± 0.07 | 0.51 ± 0.06 |
| 4.0     | 1.75 ± 0.01     | 13.19 ± 0.42 | 3.12 ± 0.06 | 0.53 ± 0.07 |
In this paper, we proposed an L-OGM prediction framework, LOPR, that decouples representation and prediction learning. LOPR consists of a VAE-GAN-based generative model that learns an expressive low-dimensional latent space of available sensor modalities and a transformer-based stochastic prediction network that operates on the learned latent space. Our experiments show that LOPR achieves SOTA performance, qualitatively and quantitatively outperforming prior L-OGM and video prediction architectures. We also demonstrate that our framework can be eas-

would need to be tested rigorously against potential out-of-distribution (OOD) scenarios. LOPR does not currently identify OOD inputs that may cause failures. To enable such capability, we could adopt an approach for epistemic uncertainty estimation as proposed by Itkina and Kochenderfer [78].

7 Conclusion

In this paper, we proposed an L-OGM prediction framework, LOPR, that decouples representation and prediction learning. LOPR consists of a VAE-GAN-based generative model that learns an expressive low-dimensional latent space of available sensor modalities and a transformer-based stochastic prediction network that operates on the learned latent space. Our experiments show that LOPR achieves SOTA performance, qualitatively and quantitatively outperforming prior L-OGM approaches and video prediction architectures. We also demonstrate that our framework can be eas-

Table 2: NuScenes, Waymo Open Perception, and Custom Robotic dataset prediction results.

| Model                  | NuScenes Dataset | Waymo Open Perception Dataset | Custom Robotic Dataset | Ours                  |
|------------------------|------------------|-------------------------------|------------------------|-----------------------|
|                        | IS_{t→15}(±)     | IS_{t→30}(±)                  | IS_{t→15}(±)         | IS_{t→30}(±)                  |
| ED LSTM [76]           | 8.25±0.13        | 18.96±1.59                   | 0.33±0.01             | 0.02±0.01               | 21.44±1.76             | 0.16±0.01               |
| TANConv LSTM [3]       | 8.99±0.09        | 15.23±1.34                   | 0.14±0.01             | 0.02±0.01               | 18.57±1.82             | 0.15±0.01               |
| PredRNN V2 [73]        | 13.04±0.24       | 79.95±4.44                   | 0.03±0.01             | 0.11±0.01               | 24.21±1.90             | 0.04±0.01               |
| Sim VP V2 [76]         | 11.86±0.19       | 54.09±2.87                   | 0.02±0.01             | 0.06±0.01               | 66.22±7.82             | 0.09±0.01               |
| PredNet [1, 44]        | 7.01±0.14        | 13.89±0.43                   | 0.14±0.01             | 0.35±0.05               | 23.54±8.91             | 0.15±0.01               |
| Fixed Last Obs Frame   | 11.50±0.14       | 14.41±1.18                   | 0.20±0.01             | 0.38±0.01               | 24.76±9.94             | 0.25±0.01               |

Ours                  | 8.09±0.26        | 11.48±1.38                   | 0.40±0.01             | 0.03±0.01               | 16.52±4.91             | 0.34±0.01               |
ily deployed on any robotic platform equipped with a LiDAR sensor, in contrast to most trajectory prediction approaches, which would require addressing compounding data distribution errors across modules and changes in sensor positioning. We hope that learnings from this framework open new research avenues in the L-OGM prediction field. In future work, we will explore how LOPR can be extended to perform 3D occupancy prediction, be applied to other tasks, such as occlusion inference [79] and path planning [80], and serve as a pre-training task for supervised models, such as trajectory prediction.

**Acknowledgments**

This project was made possible by funding from the Ford-Stanford Alliance.

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A Hyperparameters

A.1 Encoder & Decoder

Table 3: Representation Learning Hyperparameters

| Parameter               | Value                        |
|-------------------------|------------------------------|
| Architecture            | ResNet                       |
| Image Size              | $1 \times 128 \times 128$    |
| Latent Dim L-OGM        | $64 \times 4 \times 4$       |
| Latent Dim Camera       | $16 \times 4 \times 4$       |
| Latent Dim Maps         | $16 \times 4 \times 4$       |
| Channel Multiplier      | 2                            |
| Optimizer               | Adam(lr=0.0001)              |
| Batch size              | 24 per GPU                   |
| KL reg $\beta$          | 50.0                         |
| Adv weight $\gamma$     | 1.0                          |
| Path reg                | 2.0                          |
| Discriminator R1 reg    | 10.0                         |
| GPUS                    | 4 NVIDIA V100 32 GB          |

A.2 Prediction Network

Table 4 contains the hyperparameters for stochastic prediction. The prediction network training consists of three stages: deterministic training, low regularization training, and high regularization training. During deterministic training stage, $z_{stoch}$ is sampled from the target distribution. During regularized training, $z_{stoch}$ is sampled from the inference network.

Table 4: Stochastic Prediction Hyperparameters

| Parameter             | Value                        |
|-----------------------|------------------------------|
| Architecture          | Transformer                  |
| $d_{embd}$            | 256                          |
| $N_{enc}$             | 2                            |
| $N_{dec}$             | 1                            |
| $N_{heads}$           | 2                            |
| $d_{feed forward}$    | 128                          |
| Dropout               | 0.01                         |
| Optimizer             | AdamW(lr=0.0004)             |
| Deterministic Epochs  | 10                           |
| Low Reg Epochs        | 10                           |
| KL reg low $\gamma$   | 0.0001                       |
| KL reg $\gamma$       | 0.001                        |
| GPU                   | 1 NVIDIA RTX TITAN 24 GB     |

B Image Similarity Metric

The Image Similarity metric determines the picture distance function $\psi$ between two matrices $m_1$ and $m_2$ as follows [77]:

$$\psi(m_1, m_2) = \sum_{c \in C} d(m_1, m_2, c) + d(m_2, m_1, c)$$  \hspace{1cm} (6)

where

$$d(m_1, m_2, c) = \frac{\sum_{m_1[p]=c} \min\{d(m_1[p_1], p_1 | m_2[p_2] = c\}}{\#_{c}(m_1}}.$$

\hspace{1cm} (7)
$C$ is a set of discretized values assumed by $m_1$ or $m_2$ which are: occupied, occluded, and free. $m_1[p]$ denotes the value $c$ of map $m_1$ at position $p = (x, y)$. $md(p_1, p_2) = |x_1 - x_2| + |y_1 - y_2|$ is the Manhattan distance between points $p_1$ and $p_2$. $\#_c(m_1) = \# \{ p_1 \mid m_1[p_1] = c \}$ is the number of cells in $m_1$ with value $c$.

C Additional Qualitative Results

Figure 6 compares VAE-GAN (used in our experiments) and VAE. Samples from VAE-GAN appear more realistic and have sharper occupied cells. Besides the qualitative preferences, the choice of representation learning framework does not translate to significant quantitative differences.

Figure 6: Comparison between VAE-GAN and VAE on Nuscenes.