Generative AI for Autonomous Driving: A Review

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Abstract—Generative AI (GenAI) is rapidly advancing the field of Autonomous Driving (AD), extending beyond traditional applications in text, image, and video generation. We explore how generative models can enhance automotive tasks, such as static map creation, dynamic scenario generation, trajectory forecasting, and vehicle motion planning. By examining multiple generative approaches ranging from Variational Autoencoder (VAEs) over Generative Adversarial Networks (GANs) and Invertible Neural Networks (INNs) to Generative Transformers (GTs) and Diffusion Models (DMs), we highlight and compare their capabilities and limitations for AD-specific applications. Additionally, we discuss hybrid methods integrating conventional techniques with generative approaches, and emphasize their improved adaptability and robustness. We also identify relevant datasets and outline open research questions to guide future developments in GenAI. Finally, we discuss three core challenges: safety, interpretability, and realtime capabilities, and present recommendations for image generation, dynamic scenario generation, and planning.

Index Terms—End-to-End Learning, Scene and Scenario Generation, Motion Planning, Trajectory Prediction

I. INTRODUCTION

Generative AI (GenAI) has shown significant success in the context of text, image, and video generation. Nevertheless, the principles of generative learning extend beyond these applications. Generative learning describes algorithms that process data from a predefined source and learn to generate new data from a distribution that closely follows the source distribution. In automotive applications, this capability enables addressing problems ranging from map and scenario generation to reasoning and planning.

The automotive industry has long played a leading role in developing and applying AI based methods, particularly in computer vision tasks. While this stems in part from large-scale street scenes datasets [1]–[3], an Autonomous Driving (AD) system fundamentally relies on its ability to perceive and understand its surroundings. This involves creating an efficient environmental model that captures key details of the static context (e.g., roads, lanes, ...) as well as the dynamic context, which includes information about various agent types (e.g., vehicles, pedestrians, and cyclists). Such a model can define a static scene, in which the ego vehicle is situated. Understanding the temporal evolution of agents' intentions and movements allows the transformation into dynamic scenarios. Building this environmental model in latent space, generative models enable a range of applications, from accelerating map generation for traditional traffic simulations to creating detailed static scenes and complex dynamic scenarios. Beyond obvious use cases such as generating new image and video sensor data, GenAI can bridge the domain gap between synthetic and real data [4], [5] and either replace [6], [7] or improve [8] classical driving simulation.

Beyond scene and scenario generation, GenAI also significantly contributes to motion forecasting and planning tasks. Unlike conventional methods, GenAI-based forecasting methods can sample from the distribution of possible agent behaviors, capturing less likely trajectories, improving safety assessment.

Similarly, generative techniques are also applicable to motion planning task, where the generated data corresponds to trajectories and actions of the ego vehicle. However, while offline applications allow flexibility regarding computational resources, real-time forecasting and planning impose stricter constraints, limiting generative model choices based on execution speed and hardware capabilities.

For all of the aforementioned applications, established methods, machine learning approaches such as Imitation Learning (IL) for scenario generation and Reinforcement Learning (RL) for vehicle control already exist. Thus, evaluating new generative solutions alongside these established methods is essential to clearly understand their strengths and limitations. Such an analysis could facilitate the development of hybrid solutions that combine the strengths of individual methods.

While GenAI opens many possible directions, the automotive domain imposes unique requirements that conventional GenAI methods do not always meet. Physical, regulatory, and cultural constraints require that generated data remain consistent with real-world requirements. Equally important are

safety concerns, as failures in assisted or AD can lead to substantial costs or bodily harm. Therefore, automotive GenAI must also address rare but potentially hazardous scenarios. Finally, automotive GenAI applications often operate on low-performance systems such as embedded or edge devices. As conventional GenAI methods typically do not meet the consistency, safety or runtime requirements, specialized automotive-specific generative methods are required.

In this survey, we provide a structured overview of available automotive GenAI methods. Existing surveys explore GenAI applications in AD, focusing on specific aspects. Gao et al. [9] categorize Foundation Models (FMs) across tasks like planning and prediction. Wu et al. [10] highlight cross-modal learning, while Yang et al. [11] focus on Large Language Models (LLMs) for decision-making. Li et al. [12] explore LLMs for human-like driving. Ding et al. [13] and Wang et al. [14] focus on safety-critical scenarios and scenario diversity, respectively. Yan and Li [15] discuss GenAI in traffic modeling. In contrast to these works, we provide a more comprehensive analysis that emphasizes the dual role of GenAI in AD: traffic scene & scenario generation and AD motion prediction and planning. Additionally, we provide necessary fundamentals and review various generative methods, their applications, and potential in AD development, along with an overview of key motion datasets.

In Chapter II, we summarize the basic building blocks of GenAI, providing a clear overview of important core concepts. Chapter III introduces the generic AD stack, its relation to GenAI and relevant categorizations for GenAI in AD. Methods focusing on static and dynamic scene and scenario generation are covered in Chapter IV. Chapters V and VI consider applications for trajectory prediction and ego motion planning, whereas Chapter VII focuses on end-to-end approaches. Chapter VIII introduces related datasets. Open research questions are highlighted in Chapter IX.

II. FUNDAMENTALS

Generative models are designed to approximate an unknown data-generating process. This approximation process can be explicit, as in Normalizing Flows (NFs), or implicit, as in Generative Adversarial Networks (GANs). Generative models typically minimize one or more loss functions that measure how closely their generated distribution aligns with the true data distribution, typically in the form of divergence metrics like Kullback-Leibler or Jensen-Shannon [16]. Directly minimizing these divergences can lead to instabilities like mode collapse, where the model falls in a local minimum of the loss function, resulting in generated data with limited diversity. To address these challenges, many modern GenAI methods use auxiliary objectives. Additionally, divergence metrics often pose computational challenges. To address this, surrogate metrics can be used to evaluate model performance, by focusing on the quality and diversity rather than precise distance measurements. Finally, classical learning strategies, such as Supervised Learning (SL) or Reinforcement Learning (RL), can be used to stabilize and guide the training process of generative models. Specifically, SL for pre-training or RL for optimizing long-term objectives.

A. Methods

We provide a brief overview of key generative models relevant to this survey, and categorize them into the following two clusters:

Reversible Generative Models like Normalizing Flows (NFs), Invertible Neural Networks (INNs) and Neural Ordinary Differential Equations (NODEs) provide exact density estimation and sampling, making them particularly valuable for structured probabilistic modeling tasks where precise control over distributions is required. These methods are often slow and require meticulous architectural design. However, precise density estimation and sampling enable them to excel in domains where accurate representations of high-dimensional data are essential.

Implicit Generative Models such as Variational Autoencoder (VAEs), Generative Adversarial Networks (GANs), Diffusion Models (DMs) and Energy Based Models (EBMs) focus on learning rich latent representations or implicit distributions. They are naturally suited for tasks such as image generation due to their effectiveness in modeling and refining latent spaces. However, these models rely on approximations and do not provide exact likelihood estimates, making their training process prone to instabilities such as mode collapse.

Generative Transformers (GTs) can be combined with both implicit and reversible generative models and excel at capturing sequential or graph-structured dependencies. This makes them powerful for modeling complex spatial and temporal relationships in data.

a) Normalizing Flows (NFs) and Invertible Neural Networks (INNs): NFs are generative models that learn invertible mappings between a simple source distribution (typically Gaussian) and a complex target distribution using only target samples [17], [18]. Unlike VAEs, GANs, and DMs, NFs enable exact likelihood computation and efficient sampling. However, their training can be more challenging compared to other generative models [19]. Invertible Neural Networks (INNs) combine affine transformations with nonlinear invertible activation functions, forming a special class of NFs when differentiable activations are used. Thus, INNs leverage the generative capabilities of NFs, while also inheriting the expressive power of neural networks [20]. As a result, they can efficiently learn transformations between distributions, combining expressiveness with the reversibility required for exact density estimation and data generation.

b) Neural Ordinary Differential Equations (NODEs): ResNet [21], inspired by Ordinary Differential Equations (ODEs) discretization, applies iterative transformations. Neural Ordinary Differential Equations (NODEs) [22] extends this by directly parameterizing the right-hand side of the ODEs and solving it continuously. Building on this framework, Chen et al. [22] introduced Continuous Normalizing Flows (CNFs), which model transformations of probability distributions as solutions of ODEs. Unlike discrete Normalizing Flows (NFs), which apply transformations in discrete steps, CNFs continuously transform distributions over a defined time horizon. CNFs address a key limitation of traditional NFs: the computational expense of calculating the Jacobian

determinant for the change of variables. By operating in a continuous setting, CNFs improve computational efficiency, enabling scalable distribution transformations. Modern CNFs approaches, such as Flow Matching, leverage this advantage [23].

c) Variational Autoencoder (VAEs): Variational Autoencoder (VAEs) [24], are based on autoencoders and consist of an encoder and a decoder. The encoder maps input data into a latent space, in order to capture the underlying distribution of the data, while the decoder reconstructs the input data from this latent space. Unlike standard autoencoders that minimize only the reconstruction loss, which means that the points in the latent space that encode real data will result in highly accurate output data when decoded whereas many other samples will yield meaningless output, VAEs additionally minimize the Kullback-Leibler divergence between the latent space and a predefined distribution. This regularizes the latent space,enabling sampling of diverse and realistic outputs. However, data generated by VAEss often lack fidelity, since the most complex aspects of the training data distribution may not be fully captured during encoding.

d) Generative Adversarial Networks (GANs): Generative Adversarial Networks (GANs) [25] use a dual-network architecture of a generator and a discriminator. The generator creates data from noise and aims to fool the discriminator, which is trained to distinguish between real data from the training set and fake data produced by the generator. When the discriminator correctly recognizes the generated data as fake, the generator gets updated; if the generator manages to fool the discriminator, the discriminator gets updated instead. On one hand GANs yield very high-fidelity results [26]. The absence of a tractable loss function leads to instability and convergence problems in training. *Mode Collapse* occurs when the generator produces a limited set of highly realistic data and ceases exploring diverse outputs, focusing solely on deceiving the discriminator. That is why data generated via GANs generally present a lower diversity than the ones produced by VAEs and DMs [27].

e) Diffusion Models (DMs): Diffusion Models (DMs) [28], adapt the notion of diffusion from physics to the problem of generative learning. The model consists of two steps: forward diffusion and reverse diffusion. During the forward diffusion process, a noise distribution is incrementally added to the input data until it resembles a random noise distribution. Gaussian noise is typically used, but other distributions have been shown to reproduce the effect [29]. During reverse diffusion, the model learns to reverse the diffusion process, effectively restoring the original data from the noise. The trained model is eventually able to generate realistic data from random noise. Since DMs aim to recover the distribution of the training data, the generated outputs mostly feature high fidelity and high diversity. However, this comes at the cost of slow and computationally heavy training [30].

f) Generative Transformers (GTs): Transformers are AI models that leverage self-attention mechanisms to process input sequences. Unlike Recurrent Neural Networks (RNNs), which handle data sequentially, self-attentive models analyze the entire input simultaneously, capturing long-range dependencies more effectively [31]. The self-attention mechanism is a series of linear transformations applied to the input sequence to evaluate the so-called attention scores, i.e., a relative measure of the importance of element. [31] Normalized attention scores are then used to aggregate information from the previous part of the sequence into context-rich representations. It can be tailored for discriminative tasks like text classification or generative tasks such as sequence prediction, where models like GPT predict autoregressively based on prior context.

g) Energy Based Models (EBMs): Energy Based Models (EBMs) represent data through an energy function, which assigns a scalar "energy" value to each data configuration. Likely configurations correspond to lower energy values, while unlikely ones have higher values. This framework allows EBMs to model highly flexible, multimodal distributions, making them particularly useful for tasks where explicit probabilities are not necessary [32]. However, directly optimizing EBMs can be computationally challenging due to the intractability of the partition function. Methods like Contrastive Divergence [33], Score Matching [34], and Langevin Dynamics for sampling [35] address these difficulties. In recent years, there has been renewed interest in EBMs, with modern adaptations leveraging Deep Neural Networks (DNNs) for more expressive energy functions and improved scalability [36]. EBMs also show promise in integration with other generative modeling frameworks, such as hybrid approaches combining energy functions with diffusion [37] or flow-based techniques [38], whereas Hoover et al. [39] show a combination of Transformers with energy-based learning. For an overview of EBMs and its connections to generative models, see Carbone [40].

B. Classical learning strategies for generative models

Classical learning strategies, i.e., Supervised Learning (SL), Unsupervised Learning (USL), Reinforcement Learning (RL), and Imitation Learning (IL), mitigate training instabilities in generative models while improving divergence approximation efficiency and precision through auxiliary objectives. This section briefly overviews these techniques to support understanding of modern generative methods in AD.

a) Supervised Learning (SL): Each sample in a SL dataset consists of input features, along with either a discrete or continuous label. The goal of a SL task is to learn a function that maps input data to its corresponding label. A well-trained SL model generalizes effectively to unseen data. However, models can suffer from two common issues: overfitting, where the model performs well on training data but poorly on new data due to poor generalization, and underfitting, where the model fails to learn meaningful patterns, resulting in poor performance on both training and new data. SL is used to train generative models by providing explicit supervision for structured output generation. It serves as a pre-training mechanism for encoder-decoder architectures and aids in conditional generation tasks, such as text-to-image synthesis, as demonstrated in models like DALL·E.

b) Unsupervised Learning (USL): Unsupervised Learning (USL) involves the modeling of data without providing corresponding labels. The objective is to identify inherent

structures, patterns, or distributions within the dataset. Success in USL relies on extracting meaningful and generalizable insights, though it is inherently challenging to evaluate due to the absence of predefined labels. Variants of USL include self-supervised learning, which generates pseudo-labels from the data itself, often as a precursor to supervised tasks. Semi-supervised learning, by contrast, combines a small amount of labeled data with a larger set of unlabeled data, leveraging both to achieve improved performance when fully labeled datasets are scarce. These approaches bridge the gap between unsupervised and supervised paradigms, offering practical advantages in real-world applications with limited labeled data.

USL strategies are the foundation of deep generative models such as VAEs and GANs, which self-organize features crucial for high-quality sample generation. Self-supervision extracts meaningful representations from sequential data, essential for training large-scale generative and foundation models.

c) Reinforcement Learning (RL): RL [41] is a machine learning framework in which an agent learns to take actions that maximize a reward signal while interacting with an unknown environment. RL tasks are typically modeled as Markov Decision Processes (MDPs), which define an agent's interaction in a stochastic environment where the next state and reward depend only on the current state and action. An MDP consists of a state space representing information about the environment, an action space defining possible decisions, an unknown transition function governing state changes, and a reward function providing feedback for actions taken. A policy maps states to probability distributions over actions and defines the agent's behavior. The goal of RL is to find an optimal policy that maximizes the expected discounted cumulative reward, where future rewards are discounted to prioritize immediate rewards and stabilize learning. RL algorithms [42] are categorized as model-based if they rely on an explicit model of the environment and model-free if they learn directly from interactions [43].

RL optimizes generative models by refining generation policies via reward-based feedback, commonly used for fine-tuning language models and reinforcement-driven sampling.

d) Imitation Learning (IL): Designing reward functions for optimal behavior in complex environments, such as AD, is often impractical due to the diversity of scenarios. Imitation Learning (IL) provides a viable alternative by training agents to mimic expert behavior directly from demonstrations [44]. This section highlights three main IL paradigms. Behavior Cloning (BC) employs Supervised Learning (SL) to map states to actions. BC can suffer from the *covariate shift problem*, where differences between training and testing distributions lead to compounding errors [44], [45]. It is also prone to *causal confusion*, learning spurious correlations that result in irrational behaviors [45]. Inverse Reinforcement Learning (IRL) infers the reward function of an agent by observing expert behavior, which is then used to optimize the agent's policy via RL. This ensures consistency between training and testing state distributions, addressing covariate shift [44]. However, IRL is computationally intensive and struggles with reward ambiguity [46]. Adversarial Imitation Learning (AIM) frames IL as a game between an agent and a discriminator,

bypassing reward inference to reduce computational cost [44]. AIM excels in mimicking expert behavior but struggles with generalizing to unseen scenarios [47].

IL and its variants enhance generative models by using expert demonstrations for structured generation, aiding controllable generation and refining multi-modal models.

C. Conditioning, Prompting, Guidance

Unconditional generative models aim to generate samples from a marginal distribution $p(x)$ that most closely resembles the distribution of the training data. However, it is often more desirable to generate samples from specific subsets of the training data to enable targeted simulation. [48]. Conditional generative models introduce conditions to control the generation process. During inference, the model is enabled to generate samples from the conditional distributions $p(x \mid y)$ with respect to provided conditions y.

Conditions for predictive AD systems are based on diverse modalities. Sensor-based models typically leverage sensor inputs like images and control actions like steering [6], [49], [50], while others rely on abstract representations of trajectories or agent dynamics as waypoints and traffic signals as constraining map elements [51]–[53]. Alongside abstract representations, some methods condition the generation on handcrafted logic rules [51] and cost functions [52], [54], [55]. Frequently, text prompts provide context [6] or driving instructions [50], [56]. Generative models are typically conditioned during the training process or in a subsequent fine-tuning stage. A diverse set of methods leverage and mix of different approaches for conditional GANs [57], VAEs [58], NFs [59], DMs [52], [54], [55] and autoregressive models [60].

A complementary approach for controlling the generation process can be achieved via online gradient-based guidance. Instead of introducing the conditioning mechanism during learning, this method guides the generation iteratively at the inference stage. This allows to define the desired behavior as an objective function [52], [54], [55], or a temporal logic formula [51], without the need of additional training.

D. Modeling Uncertainty

Modeling the data generating process involves two fundamental sources of uncertainty [61]. Aleatoric uncertainty arises from inherent ambiguities in the data, like measurement noise, whereas epistemic uncertainty stems from the model's inherent limitations. Quantifying these uncertainties is an essential part of AD systems, since they affect the decision-making process of the AD system [62], [63]. Methods in uncertainty quantification typically focus on the compute-efficient estimation of the predictive uncertainty, following conformal prediction [64] or Bayesian inference [65] approaches. Recent methods additionally emphasize the robust disentanglement of uncertainty into aleatoric and epistemic components [66]. These methods include, for example, sampling-based techniques, such as deep ensembles [65], Monte Carlo (MC) Dropout [67], Stochastic Weight Averaging Gaussian (SWAG) [68], Laplace [69] or variational approximations of Bayesian neural networks [70], and deterministic uncertainty estimators [71], [72], such as

spectral normalized Gaussian processes [73]. In this context, generative models have been used to explicitly model epistemic uncertainty as a distribution of latent variables [74]–[76].

First research also stresses the importance of tailoring uncertainty quantification to the generative modeling itself to characterize the reliability of generations. Consequently, methods for VAEs [77], DMs [78] and GTs [79]–[81] are used to delineate whether hallucinations, inconsistencies or reproduction errors can be attributed to model limitations or inherent ambiguity in provided conditions.

III. THE AUTONOMOUS DRIVING STACK

A. Components of an AD Stack

A typical AD stack usually consists of three modules (see Fig. 1): perception, prediction and planning [82], [83]. In addition to these modules, the AD stack relies on two hardware modules: sensors that collect raw data (cf. III-B1), and control that refers to the actuation of the car.

a) Perception module: Perception is about turning the raw sensor data into an intermediate representation of a higher abstraction level, such as occupancy grids, bounding boxes etc. GenAI can be used here to create virtual scenes or scenarios (Sec. IV), represented by either sensor information (e.g. images or videos), or directly as intermediate representation.

b) Prediction module: This module predicts the future states of traffic participants based on the intermediate representation. This usually means forecasting trajectories, but auto-regressive approaches using static scene forecast are also viable. GenAI can serve as a proposal generator (Sec. V). Additionally, a self-localization and/or mapping step may be integrated into prediction if the system relies on an (external) map.

c) Planning module: This module computes a feasible trajectory for the ego vehicle, based on the current scenario and the expected trajectories of other participants (Sec. VI). In addition to using GenAI as a trajectory proposal generator for conventional planning methods, it is also possible to use GenAI as a planner directly, considering the scenario and trajectories as a form of conditioning.

d) End-to-end driving: Instead of designing independent modules, it is also possible to use a single system (Sec. VII). This means, the ego motion is directly computed, based on raw sensor data. This system can also designed in a modular fashion, with a module for each sub task, but still as a network.

B. Definition of Categories

In the following, we shortly discuss some relevant dimensions to differentiate GenAI approaches for AD.

1) Input Modalities: Generative models for AD often rely on a variety of sensors to perceive the vehicle's surroundings or an abstract representation of them. While RGB camera images are commonly used, combining them with other modalities – such as LiDAR or radar point clouds – provides robust, multimodal data for enhanced perception [84], [85]. The integration of GPS coordinates and motion and orientation information from the IMU can further enhance navigation and pose estimation [86], [87].

Strategies to fuse these modalities are classified into early, late, or mid fusion. Late fusion processes input modalities separately before merging, enabling tailored processing for each. Early fusion concatenates raw inputs or extracted features into a joint representation, fostering cross-modal correlations. Mid fusion combines elements of both, merging modalities at an intermediate stage [88], [89].

Additional rich context from static and dynamic sources, such as High Definition (HD)-Maps and occupancy grids, can be incorporated to further refine the model's understanding of the environment. HD-Maps provide precise geometric and semantic data to support vehicle localization, perception, and navigation [90]. Annotated with attributes like lane topology, they offer rich static information on street networks and environments, often including instance embeddings [91], [92]. Vectorized scene representations, unlike rasterized maps, enhance computational efficiency and include geometric street topology, instance-level details [93]–[95], and dynamic objects [93], [96]. 3D Occupancy Grids capture the volumetric state of the environment, classifying each voxel as free, occupied, or unobserved, with occupied voxels optionally carrying semantic labels [97], [98]. Birds-Eye-View (BEV) maps are a unified top-down representation of the surrounding environment, partially addressing the challenges resulting from occlusions [99]. Natural language can serve as an additional input for contextual guidance by enhancing interpretability and enabling more flexible interactions with AD systems [100], [101]. Past driving experiences from memory can extend the inputs in a temporal dimension. The input data are mapped into a latent space directly or encoded into a format with reduced dimensionality by models like Vision Transformer (ViT) [102] for image-based data, PointNet [103] for LiDAR pointclouds, or the Q-Former [104] for a joint representation of both image and text data.

2) Static and Dynamic Contexts: In AD, the surrounding context is divided into two categories i.e.: static and dynamic contexts. The static context comprises the surrounding elements which are static across time. Such elements include road maps, parked vehicles, lane boundaries, pedestrian crossings, construction sites, traffic signs etc. The dynamic context, takes into account the scene elements that are not static and change their location or state. Road traffic including moving vehicles, pedestrians, bicycles etc. falls under this category. Traffic lights are also considered as dynamic contexts [105], [106].

3) Marginal vs Conditional vs Joint Motion Prediction: The motion prediction task (c.f. V) can be subdivided into three categories: Marginal, conditional, and joint, based on the interaction modeling of the agents in the scene. Marginal motion prediction [101], [105], [107], [108], also referred to as marginal distribution, proposes multi-modal trajectories for every agent in the scene based on the static and dynamic context information in the previous time steps. In marginal motion prediction, the interactions that might arise among neighboring agents are ignored. A workaround to this issue is to generate conditional motion prediction only for the ego vehicle by assuming fixed trajectories of the neighboring agents [109], [110]. This assumption does not hold in the case of highly dynamic traffic situations, where the motions of
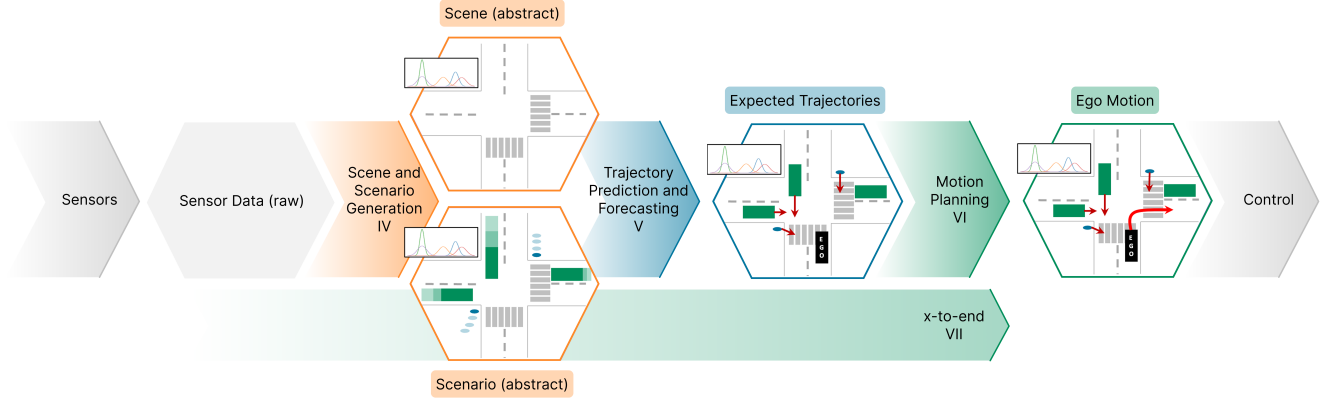
Fig. 1: The Autonomous Driving (AD) stack.

neighboring agents affect each other. To this end, joint motion prediction is necessary, where the interaction among multimodal proposed trajectories of all the agents in a scene is modeled for future time steps.

Several approaches have been proposed in recent years to model the interaction among future time steps for joint motion prediction. The work by Park et al. [111] models such interactions by leveraging the ground truth trajectories information as a part of training input. The drawback of such an approach is that ground truth information is not present during inference, which increases the probability of out-of-distribution inputs during inference. A study conducted by Luo et al. [112] models joint distribution by computing the pair-wise interaction among all agents in the scene via graph attention. A limitation of this approach is that it is computationally expensive in dense traffic environments, as the number of pair-wise interactions increases exponentially with the number of agents in the scene. The work by Zhou et al. [113] aims to reduce the computational cost in pair-wise interaction through a hierarchical attention mechanism by decomposing the scene into local regions. An alternative body of work [114], [115] proposes an implicit latent variable model for characterizing joint distribution over future trajectories. The approach encodes the dynamic scene into a latent space and samples multiple futures in parallel. The authors claim that such latent space encoding captures the unobserved scene dynamics and effectively models the joint distribution. Another approach by Nigam et al. [106] takes inspiration from Transformer architecture [31] and models the joint distribution in a factorized manner across time and agents through a Multiheaded attention mechanism. Similarly, Girgis et al. [116] combine the idea of Transformer [31] with latent variable model [114] for joint motion prediction. A generalized idea of the presenting marginal, conditional and joint prediction is shown in Figure 2.

IV. SCENE AND SCENARIO GENERATION

Scene and scenario generation is a key enabler for developing and validating AD systems. The size of the scenes can vary significantly, ranging from larger environments such as virtual cities to the immediate surroundings of an ego vehicle. Moreover, effectively modeling road users in terms of their intentions and motion is critical for transforming static environments into realistic, time-evolving scenarios. A scenario specifically describes the temporal development between multiple scenes, where each scene provides a snapshot of the environment at a given time. Every scenario begins with an initial scene, and its progression can be guided by specified actions, events, goals, and values. This temporal aspect distinguishes a scenario, which spans a period of time, from a scene, which describes a single point in time or a limited snapshot [117]. This section addresses three core dimensions of generative scene and scenario creation. First, we explore methods for producing highly detailed static maps of road networks and infrastructure. Second, we consider temporal and dynamic aspects, focusing on multi-agent interactions and realistic behavior over time. Finally, we examine world models, which integrate both static and dynamic elements into a predictive framework of how the environment evolves.

A. Static Map Generation

Static maps serve as a foundational layer of information, detailing the structural aspects of road networks, landmarks, and other environmental features. They provide essential context for autonomous vehicles and advanced driver assistance systems. They include information such as road geometry, lane markings, traffic signs, intersections, and other permanent or semi-permanent features. As they are more accurate and contain more information than typical maps, they are often referred to as HD-Maps [118], [119]. Typically, HD-Maps have been generated using mapping sensor suites like LiDAR [120], camera [121], radar [122], aerial imagery [123], and also through manual annotation [124]. However, these approaches typically require significant labor resources and involve substantial costs. Recent research also explores models that generate maps of the current environment in real-time, conditioned on live sensor data, to ensure that the maps

(a) Marginal prediction   (b) Conditional prediction   (c) Joint prediction
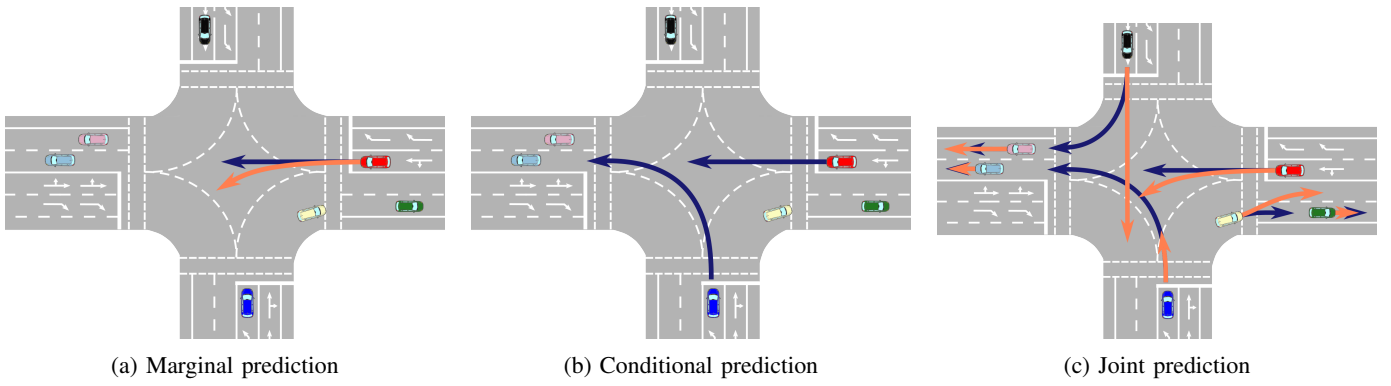
Fig. 2: Comparison of prediction types in a traffic intersection scenario. Blue and orange colors represent different prediction modes. The subfigure (a) shows marginal prediction for the red vehicle, (b) illustrates the conditional prediction of the red vehicle dependent on the ego vehicle (shown in blue), and (c) shows joint prediction, where blue and orange colors represent an entire scene independently.

remain up-to-date and accurately reflect the current state of the environment [93], [125].

Static maps are also integral to creating realistic city modeling and simulation environments for testing and validation of AD functions. Such simulations rely on these maps to replicate real-world conditions. While these maps need to be highly detailed, they do not need to correspond to actual locations in the real world. They only need to be plausible and sufficiently detailed in a data-driven manner. This differs significantly from HD-Maps used by autonomous systems, which are required to precisely represent real-world conditions.

Generally, the application of generative models to generate maps in the automotive context can be divided into three separate tasks: road layout generation, HD-Map generation, and HD-Map generation conditioned on explicit sensory input.

Road topology generation involves creating structured representations of road networks, capturing their layout and connectivity. Some works extract road topologies from aerial images [126], [127], but these approaches are constrained by the spatial resolution of aerial images and cannot generate new topologies conditioned on existing city styles. To overcome these limitations, Chu et al [128] propose Neural Turtle Graphics, a sequential generative model that iteratively creates new nodes and edges that are connected on a graph to generate a plausible city road layout. This method is used to generate natural road layouts based on existing or completely novel city styles. Previous methods focus on generating plausible road layouts, other methods extend this to the generation of detailed HD-Maps. In [129], the authors introduce HDMapGen, a set of autoregressive models that generate high-quality and diverse HD-Maps in a data-driven manner. They explore sequence-based, plain graph, and hierarchical graph representations, finding that the hierarchical approach best preserves the natural structure of HD-Maps. This two-level model includes a global and a local graph decoder, employing recurrent Graph Attention Networks and multi-layer perceptrons to produce two separate graphs. Evaluation focuses on topology fidelity, geometry fidelity, urban planning features, and diversity.

The method of generating lane graphs from HD-Maps can also be directly integrated into end-to-end driving sim-

ulators. For example, SLEDGE [130] generates lane graphs and improves on the quality and scalability of HDMapGen. In addition, agents are jointly and in parallel generated to directly simulate traffic behavior on the generated lane graph. A scene is first rasterized and encoded into a state image. Afterwards, a learned raster-to-vector autoencoder is used to represent the scene as a rasterized latent map. Subsequently, a latent DMs is used to generate either a novel scene or extrapolate existing scenes via inpainting [131] by diffusing on only a subset of input tokens. Finally, traffic participants on the generated scene are simulated using the Intelligent Driver Model [132]. Similarly, DriveSceneGen [133] generates and simulates both static map elements and dynamic traffic participants in a two-stage model. It uses an image-space DMs to generate a rasterized BEV representation of a scene. Following, a graph-based vectorization algorithm transforms the representation into a vector format. In the second stage, agents are simulated and multi-model behaviors are predicted with the Motion Transformer Model [134].

Diffusion Methods have been successfully employed in generative modeling of diverse domains like images, video and LiDAR pointclouds. Techniques like SLEDGE or DriveSceneGen rasterize scenes to leverage established diffusion techniques in 2D image space and demonstrate, that generative models can be used to generate new static scenes for simulation purposes. PolyDiffuse [135] shows that DMs can be also used for a structured reconstruction task of set elements like polylines and polygons. With a Guided Set DMs vectorized HD-Maps are created through a generation process conditioned on visual sensor data. Guidance networks are introduced to control the noise injection to prevent the permutation of the set elements from getting lost in the diffusion process. In the standard diffusion process, different permutations of a sample gradually become indistinguishable as the process progresses. Therefore, specific noise is injected at the element level with Guidance Networks. The reverse diffusion process denoises an initial proposal which is either from a human annotator or a task-specific method like MapTR [93], [136] to reconstruct and refine a HD-Map conditioned on visual sensor data.
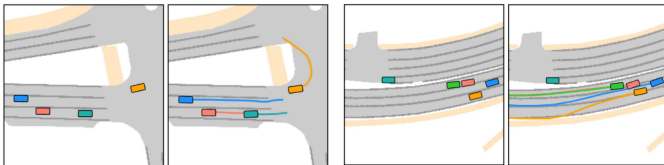
The development of generative models for static map gener-

ation has significantly advanced beyond traditional methods. However, the field remains in its early stages, with limited models addressing the diverse challenges of HD-Map generation for both simulation and real-time AD applications. Further research is essential to improve scalability, enhance real-time capabilities, and condition map generation conditioned on diverse inputs.

B. Generation of Temporal and Dynamic Aspects

Recently, various methods have been developed to generate and modify the dynamic aspects of driving scenarios, offering different levels of control and realism.

In TrafficGen [137], scenarios are generated using an encoder-decoder architecture that represents driving scenarios in a vectorized format. This allows for both the creation of new scenarios and the modification of existing ones by adding new agents or altering the trajectories of current ones. However, this method has limitations, as the user lacks control over the quality or specific properties of the generated scenarios, which is a common issue with auto-encoding of training data. In this respect, RealGen [138] (cf. Figure 3) goes one step further by generating scenarios that closely resemble a query scenario (e.g., U-turn or lane change). Additionally, it employs Retrieval-Augmented-Generation (RAG), ensuring that the generated scenario is not only similar to the query but also to the K-nearest Neighbors (KNN) of the query in external datasets, which were not seen during training. The highest level of control over scenario generation is achieved with approaches like LCTGen [139]. Here, users can generate a new scenario (cf. Figure 4) or modify an existing one using a text prompt. The crux of the approach is leveraging LLMs through advanced prompt engineering to convert textual descriptions into a representation where each agent and the map are described by a few parameters. Specifically, each agent is characterized by parameters that model its position and direction relative to the ego-vehicle as well as its future actions. Similarly, the map is defined by numbers that describe the number of lanes and their positions relative to the ego-vehicle.

(a) Initial position: left-hand side image. Tag: *U-Turn*

(b) Initial position: left-hand side image. Tag: *Lane change*

Fig. 3: Demonstration of scenario generation starting from an initial position and a tag. Images were taken from [138].

C. World Models

Maps and bounding boxes are handcrafted abstractions of driving scenarios. The generation of comprehensive and detailed scenarios necessitates world models. The concept of world models can be traced back to various disciplines,
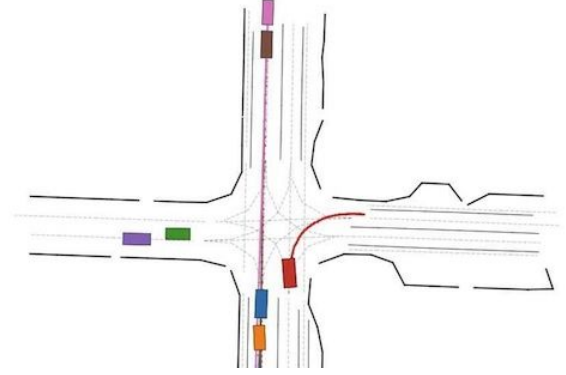

Fig. 4: Demonstration of text-prompt to scenario generation: image was taken from [139]. Prompt: *The scene is very dense. There are only vehicles on the left side of the center car. Most cars are moving in fast speed. The ego-vehicle turns right.*

e.g., mental models [140], [141] in psychology, forward models [142] in control theory, and environment models [143] in model-based RL. Ha and Schmidhuber pioneered integrating these concepts by training an AI agent to play video games [144], which is widely regarded as the seminal paper that directly references the concept of the world model.

Although world models have recently been applied to various tasks, such as video generation [6], occupancy prediction [145], and motion planning [146], the definition of world models remains unclear. Generally, a world model is characterized by the following: first, it serves as a latent representation of the environment in which the agent operates. For autonomous vehicles, the "world" refers to the real world, while for video game agents, it refers to the virtual universe of the respective game. Second, the latent representation can evolve. In other words, a world model is capable of inferring the next state of the world based on current and past latent states. It is commonly referred to as forecasting or prediction. World models can also be designed to forecast under various conditions, such as ego actions and natural language descriptions, being tailored to different application scenarios. Some researchers have set higher expectations for world models. Yann LeCun believes that a world model should grasp common sense in the world, such as the fact that objects do not spontaneously appear or disappear and that the movement of objects adheres to the laws of physics [147]. These common-sense principles collectively define how the world works. It can be seen as a crucial distinction between ordinary predictive models and world models.

Early world model studies [144], [148], [149] focus on RL in simulations and video games, typically using Convolutional Neural Networks (CNNs)-based autoencoders for environmental representation. The seminal work [144] employs an RNN to predict the next latent state based on actions, enabling recursive forecasting without real-world interaction, while incorporating a Mixture Density Network to model uncertainty. PlaNet [149] introduces the recurrent state-space model (RSSM) to separate stochastic and deterministic components, improving long-term prediction. The Dreamer

series [148], [150] advances these models, training action and value functions in the latent space with high sample efficiency.

In AD, the observation of the world can be multi-modal, e.g., images, point clouds, text, and annotations. GAIA-1 [6] employs USL with images and text as the input to the world model. It suggests that learning high-level abstract instead of low-level textures of the image is important to model the world. It distills an image tokenizer from DINO [151] to ensure a meaningful image representation. The image tokens can further fuse with text and action tokens and predict the future auto-regressively using Transformers. A concurrent work DriveDreamer [152] additionally uses annotated bounding boxes and HDmaps as inputs, which lightens the need for training data amount. Followups improve DriveDreamer in multi-view video generation, scene manipulation, and reconstruction [56], [153]. ADriver-I [154] adopts similar concept of GAIA-1, but trains a multi-modal LLMs on a private dataset to encode the image and text inputs. Comparing with GAIA-1, ADriver-I explicitly outputs the control signal accompany with the future video, enabling motion planning. Think2Drive [155] applies the model-based RL method DreamerV3 [150] to AD in the simulator CARLA [156]. Drive-WM [146] employs world models to forecast the future with diverse ego maneuvers, resulting in a decision tree. It samples the action with the highest reward, which aims to keep a safe distance to other objects and drive within lanes. Section VI provides more planning related literature. LAW [157] supervises the world model in the latent space. Similar to JEPA [147], LAW predicts the next latent state of the world and compares it with the real embedding at the same timestep. Some other works [158], [159] represent the latent world in a 2D space to facilitate learning spatial information, where BEVWorld [158] predicts multiple timesteps in parallel instead of auto-regression. 3D occupancy is another representation of the world, which simplifies the world and retain only semantic and geometric information. Training occupancy world models require less learning efforts than image ones, e.g., OccWorld [145] and Drive-OccWorld [160] are trained with 8 GPUs on the nuScenes dataset [161]. In contrast, image world models requires 32 or even more GPUs, and larger dataset (usually private) than nuScenes. Occupancy can also be combined with other input modalities, such as text [162]. However, the fidelity of an occupancy world model relies on the quality in converting sensor data to occupancy voxels. World models open new possibilities for AD, including generating realistic training data, discovering rare scenarios and corner cases, and providing a unified approach to prediction and planning. However, key challenges remain, such as assessing the validity of generated scenarios for training AD models, measuring the accuracy of the modeled world, and improving the data efficiency of training world models.

V. TRAJECTORY PREDICTION AND FORECASTING

The actions of a self-driving vehicle are interdependent with the predicted future states of surrounding traffic participants, creating a causal influence where each agent's decisions and movements are contingent upon the anticipated maneuvers of others in the shared environment. There are various approaches to address this problem. Some methods focus on trajectory forecasting of a single agent, also known as marginal prediction. In contrast, joint prediction aims to predict the trajectories of multiple participants in a mutually consistent manner(see Section III-B3 for details). Modeling the forecasting involves predicting k likely future maneuvers for a given scenario, along with their associated probabilities.

A. Prediction as a Joint Motion Forecasting Task

a) Transformer-based Approaches: Models such as Wayformer [163], Actionformer [164], RedMotion [165] and JointMotion [166] can process entire traffic scenes, including lane geometry, past actor observations, and traffic modalities (e.g., traffic light status), through their factorized attention methods to predict trajectories. While traditional methods use marginal probabilities to predict trajectories for the target actor, it has been shown that joint probability prediction is more effective for motion prediction tasks, as it avoids trajectories that result in collisions between actors. In [167], interactions, map information, and vehicle data, encoded as numerical codes from natural language descriptions, are embedded in a feature extraction module. These features are aggregated through multi-head cross-attention operations to fuse the map and interaction features into vehicle features, which are subsequently used for trajectory generation. In [168], a multi-head cross-attention mechanism is used to extract interactive information for highway scenarios. The simple topology of highways allows for the omission of map features. Long Short-Term Memory (LSTM) networks encode the information for each group of vehicles in each lane. In the cross-attention mechanism, the target vehicle information is contained in the query, while key and value represent the information of the surrounding vehicles. In general, the cross-attention mechanism is a common framework for modeling interactions in the literature, as shown in the two works mentioned above.

b) Autoregressive Modelling: Autoregressive modelling approaches factorize the distribution over past motion sequences as a product of conditionals. This factorization preserves the natural temporal causality found in motion sequences and allows to model the interaction between agents and environmental elements (e.g. traffic lights) at every step of the conditional roll-out. Early pioneering works, such as SocialLSTM [169], MFP [170] and Wavenet [171] adapted this approach with RNNs. However, their adaptation slowed due to training instabilities. The necessarily sequential roll-outs lead to cumulative errors, which made it difficult to capture long-term dependencies, and resulted in high sampling latencies.

The success of autoregressive Transformers architectures in the Natural Language Process (NLP) domain sparked a renewed interest. Drawing inspiration from sequence-to-sequence architectures in the NLP domain, multiple autoregressive Transformer encoder-decoder architectures have been proposed, including LatentFormer [172], StateTransformer [173], MotionLM [60] and AMP [174]. These models combine domain-specific encoding strategies, e.g. from other state-of-the-art models such as Wayformer [163] or MTR [175],

with decoding strategies from the NLP domain. The use of tokenization allows the representation of input and output in a unified space and the advances from the NLP domain in the design of attention mechanisms, training objectives and sampling techniques lead to direct improvements in training stability and sampling latencies. Trajeglish [176] discretizes trajectories into GPT-like small vocabulary token set, which are then autoregressively predicted using discrete sequence modeling methods. It depicts that language like encoding can be extended for application in motion prediction domain. Apart from using language like tokenizers, motion tokens as words in natural language can be used to make motion forecasting model's hidden states interpretable, and to control the motion forecasts [177]. Finally, [178] proposes a unified framework based on mixture models to predict or generate traffic behavior, including continuous models and discrete GPT-like models as special cases. [179] uses the motion tokens collected from multiple datasets to train a causal-decoder transformer to predict the next tokens showcases the inference effectiveness of these models without comprimising on the model performance reiterating the effectives of GPT like causal decoder models. The unified framework is used to explain the causes for the performance gains of GPT-like models, and transfers these insights to other models within the unified framework.

c) Diffusion Models (DMs): Recent research has explored the capabilities of DMs in trajectory prediction and generation, highlighting their versatility and effectiveness. Various DMs with distinct objectives have been introduced to cater to specific needs within these domains.

One straightforward approach proposed in MotionDiffuser [52] and DICE [180], involves adding positional noise to trajectories. These models comprise two main components: the encoder and the denoiser (decoder). The encoder processes the environmental context into encoded information that conditions the denoiser. The denoiser then estimates the noise level present in a noised future trajectory and works to remove this noise, effectively predicting the trajectory. Building on the idea of "stable diffusion" [181], [182] employs an autoencoder to reconstruct traffic scenes. It utilizes a stable DMs to denoise the encoded environmental information in the latent space. The model can effectively sample Gaussian-distributed noise during inference, iteratively denoise the samples, and reconstruct accurate trajectories. In another work, [51] represents trajectories as sequences of actions and states. It employs DMs to denoise the actions, thereby reconstructing the trajectory. This method underscores the flexibility of DMs in handling different representations of data for trajectory prediction.

The aforementioned works [52] and [51] outline another benefit of DMs with respect to control of the trajectory generation process. Besides conditioning on the scene representation in order to produce scene-consistent trajectories, these works make use of an online gradient-based guidance mechanism during the diffusion process for controllable trajectory generation. Originating from Diffuser [183], the key idea is to use the gradient method during the denoising process in order to meet high-level specifications for the generated trajectories. While [51] introduces guidance to meet safety and traffic rules specified by Signal Temporal Logic (STL) formulas [184], the

work in [52] provides a framework for performing controlled trajectory sampling based on attractor or repeller functions on the goal position. Another work in [55] develops a method to enhance diversity of traffic scenarios for AD. Among others, it proposes a pursuit-evasion game in the guidance policy in order to generate safety-critical multi-agent trajectories. In [185], an attention-based diffusion network is proposed. Interactions are incorporated into the denoising process using cross-attention across all agents at each decoder layer. The Multi-Agent Diffuser, proposed by [186], integrates DMs for generating multi-agent scenarios. Interactions are included in the diffusion process by incorporating information about other agents' decisions into each agent's trajectory vector.

Based on advances in Flow Matching (FM) in [187], [188] has shown that conditional FM is a viable alternative to DMs for trajectory prediction greatly reducing computation time.

These advances illustrate the potential of DMs in improving the accuracy and reliability of trajectory prediction and generation, making them invaluable tools in fields requiring precise motion forecasting and environmental understanding.

d) Energy Based Models (EBMs): With regard to automated driving prediction tasks, EBMs have been successfully applied to pedestrian motion prediction. [189] introduces an approach for predicting human trajectories using EBMs. The authors present a latent belief mechanism that captures uncertainty and interactions among agents. In [190], the Sequence Entropy Energy-based Model (SEEM) is proposed that is composed of a LSTM-based generator network and an energy network to determine the most representative trajectory. The more recent paper [191] addresses the challenge of predicting pedestrian trajectories in uncertain environments taking a hybrid approach combining DMs and EBMs. The method includes the use of EBMs to represent potential future trajectories and a denoising strategy that refines these predictions. The energy plan denoising technique helps to filter out less likely trajectory options, resulting in more accurate predictions.

VI. MOTION PLANNING

In this section, we discuss state-of-the-art motion planning methods and examine how generative models can enhance them within the traditional AD stack taking the abstract data input from the perception and prediction module. This section focuses solely on methods for the traditional AD stack while the following section (VII) discusses End-To-End architectures and the challenges they address within the traditional stack. The goal of planning is to determine an appropriate behavior for an autonomous vehicle considering the current state of the vehicle and the environment and key criteria such as comfort, safety and feasibility. The inherent uncertainty in the environment representation requires receding-horizon planning that continuously recalculates the motion plan with updated information making it essential that planning approaches are able to run in real-time.

A. Overcoming Conventional Planner Challenges

In recent years, traditional planning methodologies have been widely adopted, which can be broadly classified into

two approaches. On one side are the optimization-centric methods, predominantly featuring Model Predictive Control (MPC) techniques [192]–[194]. On the other side are search and sampling-oriented approaches, which include various algorithms such as A*-based, lattice-based planners, Monte Carlo Tree Search, and Rapidly-exploring Random Tree-based (RRT) planning systems [195]–[197]. This is due to their ability to comprehensively account for constraint satisfaction, such as collision avoidance. However, their performance is significantly constrained by their necessary computing time. Thus, these approaches are based on many simplifications which causes limited performance e.g. due to modeling errors and limited planning horizons. Additionally, they are limited to using local optimizers, possibly resulting in undesired local optima, such as impractical maneuvers in dense traffic [198]. Search- and sampling-based methods, on the other hand, typically sample the action space and time steps coarsely, causing sub-optimal solutions hindering their suitability for dealing with highly dynamic environments [62], [199]. Although there have been efforts to incorporate model continuity into the sampling process [200], most methods remain either inefficient or suitable only for simple scenarios. One typical simplification in the modeling is ignoring the interactions in traffic by decoupling prediction from planning[201], [202]. This approach can cause autonomous agents to behave in a reactive manner and excessively cautiously or even to freeze altogether—known as the "frozen robot problem"—in environments with high interaction and uncertainty. Here, on the other hand, learning-based methods excel due to their ability to integrate the complex and uncertain nature of other traffic participants' behavior into the motion planning.

Existing learning-based methods for planning [203]–[205] leveraging RL and IL are time efficient during inference and can adapt to complex environments (which would require complex models). However, they need an exhaustive exploration of the state space during learning to perform reliably. As a result, these methods struggle with the "long-tail" scenarios outside their training data, where a lack of generalization can undermine reliability. The lack of generalization capabilities, safety guarantees and interpretability of current learning-based approaches is a concern in such safety-critical applications. Furthermore, integrating human priors into conventional systems remains challenging, as human knowledge and reasoning are expressed in language-based representations, whereas these systems primarily process numerical sensory data [206], [207].

Generative models offer promising solutions to these limitations by providing a deeper contextual understanding and robust generalization capabilities [208]. These models can incorporate multimodal knowledge, allowing them to interpret complex, dynamic environments more holistically and to generate "what-if" scenarios that support informed decision-making in uncertain conditions. Unlike conventional systems limited to numeric inputs, generative models can represent human-like priors and reasoning, enabling planning and decisions that resemble human intuition and foresight [207]–[209]. This capability allows generative models to learn complex, multimodal behavior distributions of multiple agents, making them well-suited for interactive scenarios typical in AD. As a result, generative models address many of the fundamental shortcomings of traditional and current learning-based methods, that could bring autonomous systems closer to human-level driving in complex environments.

B. Hybrid Methods

Due to the complementary advantages and disadvantages of classical planning methods and learning-based methods which were mentioned in the previous subsection VI-A, there have been several methods proposing how to combine these approaches, resulting in hybrid motion planning systems. These can be broadly categorized into two groups, i.e., into two general ideas how to combine the benefits from both worlds. The first group employs a learning-based system to substitute or enhance components of the classical planner. Approaches learn the weights of the cost function [210], [211] or further shape it [212], [213], as the cost significantly impact the planner performance e.g. in finding good long-term goals and can be challenging to tune manually. Other methods learn the state-space model's dynamics or parts of it [214]–[216] to handle unknown or complex dynamics. The second group learns high-level policies, where the trajectory is further refined with low-level model-based planner such as MPC. Methods such as [217], [218] provide high-level plans as a reference to the MPC. Similarly, safety filters [219], [220] assess constraint satisfaction in the trajectory of the learned system, potentially generating an output that minimizes the discrepancy from the trajectory while adhering to constraints. Learning-based warmstart of an MPC planner [198], [221] also falls into this group, where the learned model provides an initial guess, which is then further optimized.

Consequently, works on hybrid motion planning methods that combine GenAI and classical approaches, have been explored in recent years.

a) Generative Methods for Planner Subcomponents: Performer-MPC [222] uses a learned MPC cost function parametrized by vision context embeddings provided by Performers — a low-rank implicit-attention Transformer. This work combines the benefits of IL with robust handling of system constraints in MPC. Similarly, GANs-MPC [223] employs a GAN to minimize the Jensen-Shannon divergence between the state-trajectory distributions of the demonstrator and the imitator. This method does not require the demonstrator and the imitator to share the same dynamics, and their state spaces may have a partial overlap. In [224], LanguageMPC proposes using LLMs to generate weight matrices, observation matrices, and action biases for MPC based on textual decisions. The weights shape the cost function of the MPC. The observation matrix provides the vehicles that need to be considered as obstacle constraints in the MPC. The action bias corresponds to the action directive of the LLMs (e.g., stop) and is incorporated as an additional bias to the output of the MPC.

GenAI models the environment, within an MPC controller in [225], where the authors substituted an LSTM-based network from the BADGR method (Berkeley Autonomous Driving Ground Robot) with a Transformer model, resulting in significant performance improvement. Recent work [226]

proposed a diffusion-based approach to learning a physics-informed state-space model for MPC. The method employs a conditional DMs to capture the multimodal distribution of vehicle dynamics, enabling high-performance driving under uncertainty, thereby enhancing safety. By conditioning on current state measurements, the DMs outputs the parameters of a physics-informed neural stochastic differential equation, which is used as the state-space model within the MPC.

A DMs is used in [227] to improve MPC performance by learning both the dynamic model (or world model) of the MPC and an initial guess for the optimization procedure in the MPC tackling two major challenges in MPC. Thus, the trajectory of the diffusion-based planner output is then further refined by the MPC, considering the respective constraints and outputting a feasible trajectory.

Few works have explored the synergy of generative models and search or sampling-oriented planning approaches in the robotics field [228], [229]. CGAN-RRT* [228] combines Conditional Generative Adversarial Networks (CGANs) with the RRT* algorithm. The CGAN model generates a distribution of feasible paths conditioned on the input map, which guides the sampling process of RRT* to accelerate convergence to an optimal path. Similarly, [229] leverages NFs to learn a distribution to sample control inputs of the autonomous vehicle. This is used for Model Predictive Path Integral Control to find the optimal rollout using importance sampling.

b) Generative Methods for Trajectory Proposals: Focusing on highway driving, Wang et al. [230] combines MPC with an LLMs.The OpenAI GPT-4 API is used as the driver agent and takes as input the environment state as a textual description. The LLM outputs the desired lane, serving as input for the low-level MPC. By checking whether the trajectory is feasible, the MPC serves as a safety verifier. The work is further extended for interactive planning by integrating a state machine, which provides a rule-based framework for guiding the LLM and the prediction of the surrounding vehicles categorizing behaviors as cooperative or aggressive. This enhances safety and interpretability with which better understanding and interaction with other vehicles is possible.

CoBL-Diffusion [231] and SafeDiffuser [232] utilize the concept of Control Barrier Functions (CBFs) as a safety filter for diffusion-based planners. They refine the trajectories through a guided diffusion process while still enforcing safety constraints through the CBFs, integrating it into the denoising process, which helps predict dynamically feasible paths by, e.g., minimizing collision risks with moving obstacles. Similarly, DDM-Lag [78] adopts a Lagrangian-based constrained optimization step to integrate safe collision avoidance into the reinforcement-guided diffusion policy learning.

A two-stage hybrid planner is also introduced in [208] that combines an LLM with a rule-based planner. In the first stage, the LLMs planner processes a natural language prompt containing task instructions, perception context, ego states, and route information to select a suitable driving behavior, such as lane following, or overtaking obstacles. The selected behavior is then passed to the Predictive Driver Model Predictive Driver Models (PDMs), which is an extension of the Intelligent Driver Model. This PDMs is responsible for refining the high-level

maneuver by sampling trajectories and selecting the best one based on a minimum cost. The authors conclude in their work that this combination is able to outperform purely LLM-based and purely rule-based planners.

DriveVLM [233] enhances trajectory prediction via chain-of-thought reasoning, combining scene description, analysis, and hierarchical planning. Detected objects' 3D bounding boxes are converted into language prompts to boost spatial understanding. A two-stage hybrid planner refines low-frequency generative trajectories in real-time using a traditional planner.

LLM-A* [234] combines an LLM with the traditional A* algorithm for the planning task. The LLM provides sub-goals (high-level goals) for guiding the search based on the start state, goal state, and obstacles. The A* planner then plans a trajectory in between these subgoals, ensuring optimality and validity. On the other hand, the generative model significantly reduces the number of states explored, leading to lower computational requirements, which is the case for the A* method.

VII. END-TO-END DRIVING

This section explores how end-to-end models address limitations of traditional modular motion planning in AD. We categorize recent generative end-to-end approaches by DMs, VAEs, Transformers and LLMs, and discuss key challenges and open issues in real-world deployment.

Conventional AD architectures consist of modular pipelines with task-specific components for perception, prediction, and planning (cf. Fig. 1), where outputs feed sequentially into subsequent modules [235]–[237]. These systems are interpretable, easier to verify, and allow for failure tracing and module adjustments [238], [239]. However, modular designs are hindered by abstract, hand-crafted interfaces, limiting their ability to generalize across diverse scenarios and producing outputs like 3D bounding boxes that may be insufficient for decision-making in complex AD scenarios [156], [239], [240]. Additionally, error propagation from upstream modules, such as missed objects in detection, compromises downstream planning [156]. Lastly, these architectures struggle to account for interactions between the ego-vehicle and other agents, as the downstream propagation of information prevents direct integration of ego motion in prediction.

End-to-end AD refers to a streamlined motion planning approach that uses a DNNs to process sensor data and output low-level control signals like steering and acceleration. The model directly learns the driving task, with intermediate feature representations trained jointly, eliminating the need for complex module interfaces [239]–[242]. While most end-to-end systems use a single large network, they can also include submodules optimized jointly for the driving task [242]. Additionally, related tasks like detection, tracking, prediction, and planning are often addressed simultaneously [243], [244].

End-to-end models are considered less complex than modular pipelines, as they feature fewer intermediate representations and a streamlined architecture. These models are more robust in handling diverse scenarios, learning implicit patterns that predefined module chains may overlook. Additionally, end-to-end models are computationally efficient, benefiting from

the elimination of redundant computations and the use of a shared backbone [241], [242]. Unlike rule-based approaches, these data-driven models scale effectively with increased data and training resources, enhancing their adaptability and performance [242].

A. Current Methods

State-of-the-art end-to-end architectures for AD typically employ generative DNN backbones, often vision-centric or incorporating Transformers for attention-based spatial and temporal reasoning.

a) Diffusion Models (DMs): Recently, a number of diffusion-based methods has emerged, focusing on optimizing the sampling process from a multi-mode trajectory distribution. Diffusion-ES [245] optimizes black-box, non-differentiable objectives by leveraging a DMs to generate initial trajectories, which are evaluated using a reward function. The top-performing samples are then mutated through a truncated diffuse-denoise process, facilitating an evolutionary search while ensuring that the modified trajectories remain within the data manifold. DiffusionDrive [246] adopts a truncated diffusion policy to generate a multi-mode action distribution from a prior anchored Gaussian distribution of trajectories, effectively streamlining the denoising process and enhancing real-time performance.

b) VAEs: GenAD [53] is a video prediction model based on a latent diffusion framework, designed to learn comprehensive representations of driving scenarios. It incorporates a VAEs and Transformer blocks with temporal and spatial attention layers, enabling effective reasoning over visual inputs. For motion planning, GenAD utilizes its learned world model to predict waypoints.

c) Transformer-based Models: Transformer-based methods for ego-motion planning leverage attention mechanisms to enhance the model's ability to reason over complex spatial and temporal relationships in driving environments. UniAD [243] integrates a perception-prediction-planning pipeline, jointly optimized for the planning task. Its perception and prediction modules are implemented as transformer decoders, which propagate planning-optimized features to an attention-based waypoint predictor. SparseDrive [244] employs a parallelized approach for perception and ego-motion planning, speeding up training and runtime efficiency. PARA-Drive [247] likewise parallelizes the training of online mapping, prediction, and planning, with the planning module capable of operating independently during inference, improving efficiency. VADv2 [248] is a Transformer-based planner that uses a discretized planning vocabulary to query environmental token embeddings that besides tokens for map and other agents explicitly include tokens for traffic lights and stop signs. It generates a probabilistic action distribution, sampled through learned priors derived from driving demonstrations and scene constraints. HydraMDP [249] is a Transformer-based multimodal planner learning through student-teacher distillation, where a perception-based student model learns from rule-based and human teachers. DRAMA [250] employs a Mamba Fusion module to fuse features from camera and LiDAR BEV

images and a Mamba-Transformer to decode ego-trajectories for effectively handling long sequence inputs.

d) LLM-based Models: The advanced reasoning skills and contextual understanding of LLMs suit these models for decision making and planning units. Furthermore, by leveraging their natural language understanding capabilities, LLMs can offer explainability, addressing the broader challenge of interpretability in end-to-end models. However, it is an ongoing research problem to improve their spatial understanding and real-time feasibility. DriveGPT4 [251] adopts LLama-2 for end-to-end planning, demonstrating high predictive performance and interpretability through action descriptions and justifications using natural language. OmniDrive [252] utilizes a Q-Former3D for perception tasks leveraging 2D pretrained knowledge. CarLLaVa [253] leverages a VLM optimized for closed-loop driving, integrating spatially aligned front-view image features into a TinyLLaMA decoder with 50M parameters. It efficiently generates paths and waypoints for improved control, demonstrating outstanding performance. DriveLM [233] uses Graph Visual Question Answering, a technique that mimics a human decision making process in driving by linking different reasoning steps, such as perception, prediction, planning, behavior and motion, into a graph-based logical chain. EMMA [254] yields competitive performance in the NuScenes and Waymo Open Motion benchmarks by using Gemini's [255] world knowledge and applying Chain-Of-Thought prompting. Senna [240] combines a Large VLM with an end-to-end framework based on VADv2 [248], which generates meta-actions using reasoning and driving knowledge to guide the end-to-end model in producing precise trajectory predictions. BEVDriver [256] feeds latent BEV maps from Li-DAR and multi-view images as efficient spatial representation to an LLM, which generates future waypoints that incorporate high level decisions.

B. Current Challenges and Directions

End-to-end approaches typically rely on IL with large expert-labeled datasets. However, the closed-loop nature of motion planning in AD raises concerns about the suitability of these training methods. RL methods are becoming increasingly scalable, efficient, and robust across domains [150], [257]. However, they face challenges such as sparse rewards and weak gradient signals for training deep networks within end-to-end stacks [242]. To address this, some integrate cost functions alongside IL [249]. Model-based RL approaches, like Think2Drive [155], mitigate these issues by learning latent world models of environment transitions, used both for RL training and expert data generation to support end-to-end learning. Ma, Zhou et al. [258] illustrate that incorporating a world model significantly enhances the performance of the planning model UniAD [243]. There is an increasing number of world model planners that are end-to-end models generating driving decisions based on self-generated imagined futures [145], [146], [152], [154], [155].

Furthermore, significant challenges persist that hinder the effective deployment of end-to-end methods and generative motion planning approachees as described in section VI in

real-world applications. End-to-end motion planner evaluations rely on benchmarks for both open- and closed-loop settings, yet existing benchmarks face limitations, especially in effectively comparing learned methods to rule-based planners. Open-loop evaluation compares a motion planner's output to expert ground truth without considering vehicle or agent effects, whereas closed-loop evaluation includes dynamics and interactions, directly giving feedback on the driving behavior [208]. The failure of open-loop ego-forecasting to enhance driving performance reveals misaligned objectives of current learning-based planners [259]. A large number of state-of-the-art generative motion planning models are optimized for open-loop driving [53], [233], [244], [247], while the research community widely recognizes the need for closed-loop optimization to ensure effective evaluation. Imitation-based planners generally perform well in open-loop but lack the robust generalization of rule-based methods in closed-loop evaluation [259]. End-to-end models rarely benchmark against traditional approaches [243], [244], [246], [254] and often fail to outperform simpler methods in closed-loop settings [260].

Furthermore, closed-loop evaluation is limited by a lack of realistic, scalable simulators. While CARLA offers control, it struggles with sim-to-real gaps. NAVSIM lacks reactivity and long-term realism [260]. DriveArena improves scenario diversity but inhibits practical limitations [261]. HUGSIM [262] provides photorealistic evaluation across 70 sequences, yet faces challenges in rendering fidelity and dynamic elements like pedestrians. However, ongoing research addresses these challenges through rapid cycles of development, continuously improving simulators and models to push the limits of existing benchmarks.

VIII. DATASETS AND SIMULATORS

This section provides an overview of datasets that can be used for trajectory prediction and motion planning. We will first introduce some real-world datasets and then discuss some commonly used driving simulators that can be used to record synthetic datasets or for experiments in RL.

A. Datasets usable for above categories

Datasets with agent motion, often connected to sensor data, are of foundational for GenAI. On one hand, they are used for directly training GenAI models. On the other hand, they serve for pre-training purposes and extraction of meaningful representations of street scenes. Table I presents an overview of different motion datasets for motion forecasting or prediction and furthermore also for trajectory prediction. Additionally, it compares different properties such as the number of scenarios and the total recording time. The datasets are recorded with various sensors, including RGB camera, radar sensors, and LiDAR. Furthermore, they are preprocessed by reducing the resolution [263] or deleting recordings with onboard system failures [268]. Argoverse [264] is a dataset for motion forecasting that is recorded by LiDAR, RGB video sensors, front-facing stereo, and a 6-DOF localization. It includes data from American cities in different seasons, weather conditions, and times of a day. Argoverse is preferred recorded for 3D tracking

and motion forecasting that is required for trajectory planning. In INTERACTION [265], drone and traffic cameras were used to record scenarios. A big advantage, in contrast to the other datasets, is that INTERACTION includes unsafe maneuvers, e.g. dangerous situations which could result in an accident. Furthermore, it has diverse scenarios like highway, round-about, stopping at traffic signs, and lane changes. LYFT [266] is recorded using cameras, LiDAR, and radar sensors as well as semantical HD-Maps for the task of motion prediction. Those HD-Maps capture road rules, lane geometry, and other traffic elements. However, LYFT only provides data from the day. Similarly, Waymo [267] is a dataset for predicting the motion of other vehicles by providing 3D bounding boxes and map data. Furthermore, it provides diverse scenes in a large-scale dataset. The NuScenes [161] dataset was recorded using cameras, radar, and LiDAR to provide a $360°$ field of view. Especially the radar dataset is not commonly provided in other datasets. Additionally, NuScenes provides diverse situations like comparing left and right-hand driving. Likewise, the Yandex [268] dataset is released for motion prediction and is collected using camera-based sensors. To ensure high data quality, the raw recordings undergo preprocessing to remove scenes exhibiting onboard system failures or violating physical constraints. Additionally, it contains a wide range of scenes, including different countries (Israel, United States, and Russia), with different seasons, times of a day, and weather conditions. Yandex is also released for evaluating uncertainty estimation and robustness to domain gaps. Therefore, it provides an in-domain dataset and an out-domain dataset. Finally, Argoverse2 [263] is a dataset for motion prediction and forecasting. Besides the forecasting motion dataset, it contains a sensor dataset and a LiDAR dataset. It is recorded in diverse cities of the United States, since the traffic and also the kind of vehicles is different e.g. are there more motorcycles or cars in the traffic. Furthermore, the dataset includes different weather conditions and provides the forecasting for different vehicles like motorcycles or buses and not only cars.

B. Driving simulators

Driving simulators are a valuable option for experiments in AD to explore and analyze dangerous situations, like collision scenarios with pedestrians and other road users. Furthermore, they serve as environment in closed loop model training. Last but not least, synthetic data are cheaper than real data. In this section, we present an overview of different driving simulators, their benefits, strengths, and weaknesses. CARLA (Car Learning to act) [156] is an open-source autonomous driving simulator. CARLA is grounded on the Unreal Engine [269] and the roads and urban settings are defined by using the ASAM OpenDrive standard [270]. Since CARLA is developed for researching on AD, it provides some sensors including RGB cameras, LIDAR sensors, a ground truth sensor for semantic segmentation, and one for instance segmentation. The CARLA driving simulator can be used for many applications. For AD tasks, CARLA is used in RL [155], [271]. Furthermore, it has been used for motion prediction [272] and trajectory planning [273], [274].

TABLE I: Overview of Motion Datasets [263]

	Argoverse [264]	INTER. [265]	LYFT [266]	WAYMO [267]	NuScenes [161]	Yandex [268]	Argoverse2 [263]
# Scenarios	324 k	–	170 k	104 k	41 k	600 k	250 k
# Unique Tracks	11.7 M	40 k	53.4 M	7.64 M	–	17.4 M	13.9 M
Average Track Length	2.48 s	19.8 s	1.84 s	7.04 s	–	–	5.16 s
Total Time	320 h	16.5 h	1118 h	574 h	5.5 h	1667 h	763 h
Scenario Duration	5 s	–	25 s	9.1 s	8 s	10 s	11 s
Test Forecast Horizon	3 s	3 s	5 s	8 s	6 s	5 s	6 s
Sampling Rate	10 Hz	10 Hz	10 Hz	10 Hz	2 Hz	5 Hz	10 Hz
# Cities	2	6	1	6	1	6	6
Unique Roadways	290 km	2 km	10 km	1750 km	–	–	2220 km
Avg. # tracks per scenario	50	–	79	–	75	29	73
# Evaluated object categories	1	1	3	3	1	2	5
Multi-agent evaluation	✗	✓	✓	✓	✗	✓	✓
Mined for interestingness	✓	✗	–	✓	✗	✗	✓
Vector Map	✓	✗	✗	✓	✓	✗	✓
Download Size	4.8 GB	–	22 GB	1.4 TB	48 GB	120 GB	32 GB
# Public Leaderboard Entries	194	–	935	23	18	3	–

SUMO [275] is an open-source driving simulator for traffic scenario generation. The focus of SUMO is the research on traffic scenarios [276] as well as vehicle-to-vehicle communication [277]. For that, different complex road networks and vehicles can be analyzed. The road network can be constructed by the user itself, whereby it can decide whether to build its own network or use real road networks. Real road networks can be included by e.g. OSM [278] or XML-Descriptions. SUMO only provides a BEV on a 2D-world. In contrast to CARLA, SUMO does not provide any assets like buildings or vegetation. However, pedestrians and information about the vehicles i.e. emissions are available. SUMO is also used for RL tasks [279], [280] whereby the focus is more on the traffic scenario itself i.e. traffic light controlling as on one ego-vehicle. Furthermore, it is applied for motion prediction [281], [282] and trajectory planning [283].

TORCS [284] is a racing simulator that provides a diverse range of vehicles and maps. Additionally, it gives the opportunity to edit new maps and vehicles. Therefore, it provides a valuable basis for racing tasks in AD. Furthermore, the dynamical physics of the vehicles is realistic. Besides that, there is a lack of complexity, such that no pedestrians or intersections are provided. TORCS is a commonly used driving simulator for RL [285], [286].

IX. CHALLENGES, RECOMMENDATIONS AND OUTLOOK

A. Challenges

A diverse range of generative models, including DMs, VAEs, GTs, LLMs, and EBMs, have been explored in the context of AD, each offering unique advantages and facing inherent limitations. While these methodologies contribute to significant advancements in AD, they also introduce complex and interrelated challenges, especially regarding safety, interpretability and practical deployment in real-world driving environments.

a) Safety: Safety is paramount in deploying critical functionalities that could directly impact human lives. In automotive applications, guidelines like SOTIF [287] standardize preparations for unforeseen outcomes, incorporating verification and validation akin to rule-based models. The opacity of DNNs introduces vulnerabilities exploited by adversarial attacks [288]. Mitigation strategies involve training networks against such adversarial examples [289]. Incorporating constraints aids in learning knowledge priors [290], ensuring predictions remain within defined boundaries. Plausibility-based approaches maintain consistency with physical and environmental constraints, providing parallel safety layers [291]. Beyond use-case based testing, simulation-based methodologies, such as diffusion models coupled with RL frameworks used by GAIA [6], enhance safety validation and allow extensive in-simulation testing. Integrating these with established standards bridges traditional safety protocols and the complexities of advanced AI systems. Methods like Hamilton-Jacobi (HJ) reachability analysis [292] and CBFs serve as safety filters or certificates [293], [294] for validating the outcome of learning-based methods. However, their application faces challenges due to computational constraints in unpredictable environments. Recent advancements combine CBFs with predictive control [295] or employ hypernetworks to estimate safe sets in real-time based on environmental observations [296].

b) Interpretability: Interpreting concepts within generative models is challenging, particularly because these models often contain millions or even billions of parameters. This opacity poses risks in safety-critical domains like AD, the system behavior to inputs can be hard to predict. Interpretability paradigms are generally divided into four: behavioral, attributional, concept-based and mechanistic [297]. Behavioral interpretability addresses how models respond under various conditions and scenarios. Attributional interpretability highlights the most influential input features driving the model's output. This includes methods generating synthetic scenarios coupled with saliency analysis to attribute anomalous detections to specific scenario elements [298]. While behavioral and attributional interpretability have seen some application in AD, larger models pose greater challenges that are more effectively addressed by concept-based and mechanistic interpretability. Concept-based interpretability relies on semantically meaningful latent factors, while mechanistic interpretability reverse-engineers a model's internal processes to reveal its decision-making logic. However, the latter two approaches remain largely underexplored for AD. To the best of the authors' knowledge, only one work [177] has applied both concept-

based and mechanistic interpretability to AD. As models continue to grow in scale, we expect many more works to focus on these interpretability paradigms.

c) Real-time Feasibility: Efficient operation of generative models within real-time constraints is crucial for autonomous systems. Xu et al. [299] reviews LLM optimization strategies for training and inference, including parameter sharing, modular architectures, quantization, pruning, knowledge distillation, and low-rank factorization [300]. By using Conditional Flow Matching, Ye and Gombolay [188] achieved up to a 100x speedup for a prediction task, while [301] applied the technique for efficient robot navigation. Sparse representations are replacing dense ones, improving efficiency. Tang et al. [302] use sparse transformer-based representations to reduce computational overhead by compressing latent variables. Similarly, SparseDrive [244] introduces a sparse perception module and parallel motion planner, optimizing efficiency and safety with a hierarchical collision-aware trajectory selection strategy. Model-based RL-based approaches, like Hafner et al. [148] reduce online computation requirements by modeling latent dynamics for parallel decision making. Combining these methods with specialized hardware like TPUs and neuromorphic systems [303] can greatly boost the real-time performance of generative models.

B. Recommendations

While GenAI algorithms are advancing rapidly and often outperform traditional approaches, it remains too early to assess their long-term impact. Therefore, the primary recommendation of this section is to closely follow the latest developments in the generative model landscape.

A natural first step in following these developments is selecting appropriate GenAI models. Until recently, it was generally believed that VAEs were the worst performing model, followed by GANs, with diffusion models ranking highest in terms of image generation quality, although their computational cost were ranked in reverse order. However, recent leading architectures [181] demonstrate that VAEs can generate high-quality images when trained at scale and when their reconstruction loss is combined with GAN-like adversarial losses on patches. This highlights that hybrid solutions can achieve superior performance.

The effectiveness of these hybrid models further underscores the importance of latent spaces. Whether based on learned features, as in the VAE example, or abstractions of agents on a BEV map, the choice of latent spaces is crucial. Abstract 'engineered' representations provide clear explainability and facilitate rule-based checks, whereas learned representations typically deliver better performance and are more suitable for resource efficient end-to-end approaches [242]. However, this advantage comes with the drawback that learned latent variables are more prone to suffer from domain shifts.

For dynamic scenario generation and decision making, most models follow the autoregressive logic of LLMs, typically using the same representation or token as in scene generation. Currently, two strategies stand out: transformer and state space (MAMBA) models.

In the context of planning, traditional RL methods now compete with action transformers or action state-space models. GenAI approaches appear to be overtaking pure RL solutions, as reflected, for instance, in the CARLA leaderboard at the time of writing. Particularly, models incorporating reasoning capabilities from LLMs present a promising future direction. Nevertheless, hybrid approaches that integrate elements of traditional planning are likely to remain competitive.

Regarding training methods and data, diversity in training objectives and methods generally improves performance. Similarly, leveraging multiple diverse datasets is preferable to single-source training, provided the datasets are well curated.

C. Outlook

GenAI solutions for scene generation appear promising, but the domain gap remains an obstacle when replacing real-world data with synthetic data. Therefore, methods for measuring the domain gap in street scenes and driving scenarios must be carefully evaluated, and further development of domain-specific safety-aware metrics is essential. Additionally, detecting hallucinations and filtering of illogical outputs will be another important direction for GenAI quality assurance.

Despite the advances in GenAI for motion planning, leading algorithms in closed-loop training and testing still exhibit measurable accident rates. This underscores the need for more robust solutions. Progress will depend on refining testing methods, identifying corner cases, and re-training GenAI planners. Additionally, testing in open-loop shadow mode is necessary, alongside novel methods for evaluating proposed but unexecuted actions of GenAI agents.

The deployment of LLM-based autonomous decision making on edge devices poses new challenges, primarily due to the resource demands of reasoning models that offer some degree of explainability. While knowledge distillation shows promise in downsizing LLMs, in-depth studies in the AD domain are yet to come. End-to-end strategies, spanning from sensor input to action, go in a quite opposite direction, but they necessitate the development of novel testing and diagnostic approaches.

GenAI in AD is an emerging field, and this survey offers only an early glimpse of its potential. Despite numerous challenges and open research questions, the outlook is promising, and we remain optimistic that some of the technical trends outlined here will ultimately mature into robust solutions.

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