Goal-oriented Autonomous Driving

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Abstract

Modern autonomous driving system is characterized as modular tasks in sequential order, i.e., perception, prediction and planning. As sensors and hardware get improved, there is trending popularity to devise a system that can perform a wide diversity of tasks to fulfill higher-level intelligence. Contemporary approaches resort to either deploying standalone models for individual tasks, or designing a multi-task paradigm with separate heads. These might suffer from accumulative error or negative transfer effect. Instead, we argue that a favorable algorithm framework should be devised and optimized in pursuit of the ultimate goal, i.e. planning of the self-driving-car. Oriented at this goal, we revisit the key components within perception and prediction. We analyze each module and prioritize the tasks hierarchically, such that all these tasks contribute to planning (the goal). To this end, we introduce Unified Autonomous Driving (UniAD), the first comprehensive framework up-to-date that incorporates full-stack driving tasks in one network. It is exquisitely devised to leverage advantages of each module, and provide complementary feature abstractions for agent interaction from a global perspective. Tasks are communicated with unified query design to facilitate each other toward planning. We instantiate UniAD on the challenging nuScenes benchmark. With extensive ablations, the effectiveness of using such a philosophy is proven to surpass previous state-of-the-arts by a large margin in all aspects. The full suite of codebase and models would be available to facilitate future research in the community.

1. Introduction

With the successful development of deep learning, autonomous driving algorithms are assembled with a series of tasks1, including detection, tracking, mapping in perception; and motion and occupancy forecast in prediction. As depicted in Fig. 1(a), most industry solutions deploy standalone models for each task independently [59, 62], as long as the resource bandwidth of on-board chip allows. Although such a design simplifies the R&D difficulty across teams, it bares the risk of information loss, across modules, error accumulation and feature misalignment due to the isolation of optimization targets [50, 57, 72].

A more elegant design is to incorporate a wide span of tasks into a multi-task learning (MTL) paradigm as shown in Fig. 1(b). This is a popular practice in many domains, including general vision [69, 81, 95], autonomous driv-

1In the following context, we interchangeably use task, module, component, unit and node to indicate a certain task (e.g., detection).
ing [15, 52, 88, 92], such as Transfuser [20], BEVerse [92], and industrialized products, e.g., Mobileye [59], Tesla [76], Nvidia [62], etc. In MTL², the co-training strategy across tasks could leverage feature abstraction; it could effortlessly extend additional tasks and save computation of on-board chip. However, such a scheme may produce inconsistent estimate and cause undesirable “negative transfer” [23], leading to performance drop compared to the standalone option.

By contrast, the emergence of end-to-end autonomous driving [11, 15, 19, 37, 85] unites all nodes from perception, prediction and planning as a whole. The choice and priority of preceding tasks should be determined in favor of planning. The system should be goal-oriented¹, exquisitely designed with certain components involved, such that there are few accumulative error as in the standalone option or negative transfer as in the MTL scheme. Table 1 describes the task taxonomy of different framework designs.

Following the end-to-end paradigm, one “tabula-rasa” practice is to directly generate the planned trajectory, without any participation from perception and prediction as shown in Fig. 1(c.1). Pioneering works [14, 16, 21, 22, 68, 85, 93] demonstrate impressive performance in the closed-loop simulation [26]. While such a direction deserves further exploration, it might suffer from safety and interpretability problems, especially for highly dynamic urban scenarios. In this paper, we lean toward another perspective and ask the following question:

**Toward a reliable and goal-oriented autonomous driving system, how to design the pipeline in favor of planning? which preceding tasks are requisite?**

A gut-feeling resolution would be to perceive surrounding objects, predict future behaviors and plan a safe maneuver explicitly, as illustrated in Fig. 1(c.2). Contemporary approaches [11, 30, 37, 50, 72] provide good insights and achieve impressive performance. However, we argue that the devil lies in the details: previous works more or less fail to consider certain components (see block (c.2) in Table 1), being reminiscent of the goal-oriented spirit. We elaborate on the detailed definition and terminology, the necessity of these modules, and why they should be organized hierarchically in the Supplementary.

To this end, we introduce UniAD, a Unified Autonomous Driving algorithm framework to leverage various tasks toward a safe and robust system as depicted in Fig. 1(c.3). UniAD is designed in a goal-oriented spirit and organized hierarchically. We argue that this is not a simple stack of tasks with mere engineering effort. A key component is the query-based design to connect all nodes. Compared to the

²In this paper, we refer to MTL in autonomous driving as tasks beyond perception. There are plenty of work on MTL within perception, e.g., detection, depth, flow, etc. This kind of literature is out of scope.

¹We advocate the design philosophy to be goal-oriented; in our setting, the goal is planning. One may set the goal to be prediction, traffic flow metric in V2X, etc., depending on the actual system.

Table 1. **Task comparison and taxonomy.** “Design” column is classified based on discussion in Fig. 1. “Det.” denotes 3D object detection, “Map” represents online mapping, and “Occ.” is occupancy map prediction. †: these work do not aim for planning, and yet they still share the spirit of unified perception with prediction; the framework is devised hierarchically with insight.

| Design | Approach | Perception | Detection | Track | Map | Prediction | Motion | Occ. | Plan |
|--------|----------|------------|-----------|-------|-----|------------|--------|------|------|
| (b)    | NMP [88] | ✓          | ✓         | ✓     | ✓   | ✓          | ✓      | ✓    | ✓    |
| (c.1)  | [14, 16, 68, 85] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| (c.2)  | PnPNet† [50] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| (c.3)  | UniAD (ours) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

The contributions can be summarized as follows. **(a)** we embrace a new outlook to devise the autonomous driving framework following a goal-oriented philosophy, and demonstrate the task performance can be enhanced to a new level. Instead of standalone design or multi-task learning, certain components should opt in and be prioritized hierarchically. **(b)** we present UniAD, a comprehensive system to fully leverage a wide span of tasks. The key component to hit the ground running is the unified query design across nodes. As such, UniAD enjoys flexible representations to exchange knowledge from a global perspective. **(c)** we instantiate UniAD on the challenging benchmark for realistic scenarios. Through extensive ablations and experiments, we verify the effectiveness of our proposed framework in all aspects.

We hope this work would shed some light on the target-driven design for the autonomous driving system, providing a starting point for coordinating various tasks.

## 2. Methodology

### Overview.

As illustrated in Fig. 2, UniAD is comprised of four transformer decoder-based perception and prediction modules and one planner at the end. Queries \( Q \) play the role of connecting the pipeline to model multi-agent and scene-level contexts. Specifically, a sequence of multi-camera images is fed into the feature extractor and we transform the bounding box representation, queries allow for more flexible representations and encode rich social dynamics and interactions across agents. To the best of knowledge, UniAD is the first work to comprehensively explore the necessity of each module in the autonomous driving system. With extensive ablations and experiments, we verify the effectiveness of our proposed framework in all aspects.

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Pipeline of Unified Autonomous Driving (UniAD). It is exquisitely devised in spirit that a desirable algorithm framework for autonomous driving should be goal oriented. Instead of a simple stack of tasks, we investigate the effect of each module in perception and prediction, leveraging the benefits of joint optimization from preceding nodes to ultimate pursuit in the driving scene. UniAD is pipelined via Transformer structure, with the unified query as veins running in the loop. The map over occupancy is for visual purpose only.

2.1. Perception: Tracking and Mapping

TrackFormer. It performs joint detection and multi-object tracking (MOT) without non-differentiable post-processing. Inspired by [87, 91], we take a similar query design. Besides the conventional detection queries utilized in object detection [8, 96], additional track queries are introduced to model the life cycle of tracked agents throughout the scene. Specifically, at each time step, initialized detection queries detect newborn agents while stored track queries keep capturing information from previously observed ones. Both detection queries and track queries enhance themselves by attending to BEV feature \( B \). As the scene is updated in a sequence, track queries are also continuously updated by an attention module until the agent disappears completely (untracked in a certain time period). In this way, the track query fully aggregates the temporal information of the corresponding agent. Similar to [8], TrackFormer contains \( N \) layers and the final output query \( Q_A \) provides rich historical knowledge of \( N_a \) valid agents for downstream prediction tasks. Note that one particular ego-vehicle query is included in the query set to explicitly model the self-driving vehicle itself for future usage, which is always assigned to the ground truth of ego vehicle and not involved in bipartite matching during training.

MapFormer. We design it based on a 2D panoptic segmentation method Panoptic SegFormer [49]. Panoptic paradigm is desired here following how recent motion forecasting works discretize HD maps into elements. For example, when each lane is treated as an instance separately, its geographic location and high-level structure information could be preserved in each map query, which is essential and easily helps downstream tasks, i.e., prediction and planning, to model the relationship between road elements and agents. For autonomous driving scenarios, we set lanes, dividers and crossings as things queries, and the drivable area as stuff query. MapFormer also has \( N \) stacked layers whose all decoded results are supervised, while only the updated query \( Q_M \) in the last layer are forwarded to MotionFormer for agent-map interaction.

2.2. Prediction: Motion Forecasting

Most recent researchers have proven the effectiveness of transformer structure on the motion task [55, 60, 61, 74, 86], inspired by which we propose MotionFormer under end-to-end scenarios. With information-enriched queries for dynamic agents \( Q_A \) and static map \( Q_M \) from TrackFormer and MapFormer respectively, it predicts all agents’ multi-modal future movements (several possible trajectories) in a scene-centric manner. This paradigm produces multi-agent trajectories in the global frame in a single pass, which greatly saves the computational cost of aligning the whole scene to each agent’s coordinate [44]. Meanwhile, in order to preserve the ego identity in the scene-level setting
and make the ego feature engage in social interactions with other agents, we have an ego-vehicle query from TrackFormer passing through the motion node. Formally, the output is \( X = \{ \hat{x}_{i,k} \in \mathbb{R}^{T \times 2} | i = 1, \ldots, N_t; k = 1, \ldots, K \} \), where \( i \) indexes the agent, \( k \) indexes the modality and \( T \) is the length of prediction horizon.

**MotionFormer.** It is composed of \( N \) layers and built via the cross-attention mechanism. In each layer, we aim at capturing three types of interactions: agent-agent, agent-map and agent-goal point. For each motion query \( Q_{i,k} \) (defined later, and we omit subscripts \( i, k \) of motion queries for simplicity), its interactions between other agents \( Q_a \) or map elements \( Q_m \) could be formulated as:

\[
Q_{a/m} = \text{MHCA}(\text{MHSA}(Q), Q_A/Q_M),
\]

(1)

where MHCA, MHSA represents multi-head cross-attention and multi-head self-attention [80] respectively. In the meantime, it is essential for the forecasting task to focus on the intended position as well. Benefiting from environmental dynamics in BEV, we devise an agent-goal point attention module via deformable attention [96] as follows:

\[
Q_g = \text{DeformAttn}(\hat{Q}, \hat{x}_t^{l-1}, B),
\]

(2)

where \( \hat{x}_t^{l-1} \) is the endpoint of the prediction from previous layer, a deformable attention module \( \text{DeformAttn}(q,r,x) \) takes in the query \( q \), reference point \( r \) and dense feature \( x \). By sparsely sampling the encoded BEV feature near the agent’s goal point, we refine the predicted trajectory with its surrounding information. All three interactions are finally fused via concatenation and a multi-layer perceptron (MLP), resulting in query context \( Q_{ctx} \) which is sent to the proceeding layer or decoded as prediction results.

**Motion queries.** The input queries for each layer of MotionFormer referred to as motion queries are comprised of two components: the query context \( Q_{ctx} \) produced by the last layer and the query position \( Q_{pos} \). Since the scene-centric paradigm brings extra degrees of freedom and uncertainty which lifts the challenge for prediction, it is crucial to encode the positional information into motion queries. Specifically, \( Q_{pos} \) captures the positional knowledge in four-folds as Eq. (3): (1) the position of scene-level anchors \( I^s \); (2) the position of agent-level anchors \( I^a \); (3) current location of agent \( i \) and (4) the predicted goal point.

\[
Q_{pos} = \text{MLP}(\text{PE}(I^s)) + \text{MLP}(\text{PE}(I^a)) + \text{MLP}(\text{PE}(\hat{x}_0)) + \text{MLP}(\text{PE}(\hat{x}_t^{l-1})).
\]

(3)

Here the sinusoidal position encoding \( \text{PE}(\cdot) \) followed by an MLP is utilized to encode the positional points and \( \hat{x}_0^a \) is set as \( I^s \) at the first layer (subscripts \( i, k \) are also omitted). The scene-level anchor represents prior movement statistics in a global view, while the agent-level anchor captures the possible intention in local coordinate. They both are clustered by k-means algorithm on the endpoints of ground-truth trajectories, to narrow down the uncertainty of prediction. Contrary to the prior knowledge, the start point provides customized positional embedding for each agent, and the predicted endpoint serves as a dynamic anchor optimized layer-by-layer in a coarse-to-fine fashion.

**Non-linear Optimization.** Contrary to the conventional motion forecasting works which have access to ground truth perceptual results e.g. bounding boxes, we consider the prediction uncertainty from prior stages in our end-to-end paradigm. Brutally regressing the ground-truth trajectories from an imperfect detection position or heading angle may cause unrealistic results with large curvature and acceleration which are hard for vehicles to follow. To tackle this, we adopt a non-linear smoother [7] to optimize the target trajectories:

\[
\hat{x}^* = \arg\min_x c(x, \hat{x}),
\]

(4)

where \( \hat{x} \) and \( \hat{x}^* \) denote the original and optimized target trajectory, \( x \) is generated by multiple-shooting [3], and the cost function is as follows:

\[
c(x, \hat{x}) = \lambda_{\text{xy}} |x - \hat{x}|_2 + \lambda_{\text{goal}} |x_T - \hat{x}_T|_2 + \sum_{\phi \in \Phi} \phi(x),
\]

(5)

where \( \lambda \) is a hyperparameter, the kinematic function set \( \Phi \) has five terms including jerk, curvature, curvature rate, acceleration and lateral acceleration. We optimize the target trajectory to ensure vehicles drive to the goal and obey kinematic constraints. This process is performed during training to get reasonable targets only and does not affect inference.

### 2.3. Prediction: Occupancy Prediction

Occupancy grid map is a discretized BEV representation where each cell holds a belief indicating whether it is occupied, and occupancy prediction task is designed to discover how the grid map changes in the future. Previous approaches predict results with the help of RNNs for temporally expanding future predictions from observed BEV features [34, 37, 92]. However, they generate per-agent occupancy masks through highly hand-crafted clustering post-processing. The lack of explicit agent knowledge inside the network makes it difficult to model agent-level actions, which is essential to understand how the scene evolves. To address this, we present OccFormer to incorporate both scene-level and agent-level semantics in two aspects: (1) a dense scene feature acquires agent-level features via an exquisitely designed attention module when unrolling to future horizons; (2) we produce instance-wise occupancy easily by a matrix multiplication between agent-level features and dense scene features without heavy post-processing.
Specifically, OccFormer is composed of $T_o$ sequential blocks where $T_o$ indicates the prediction horizon and is typically smaller than $T$ in the motion task due to the high computational cost of densely represented occupancy. Each block takes the informed agent features $G^t$ and the state (dense feature) $F^{t-1}$ from previous layer as input, and generates $F^t$ for timestep $t$ considering both instance- and scene-level information. To produce agent feature $G^t$ with dynamics and spatial priors, motion queries from MotionFormer are max-pooled in the modality dimension to get a more compact representation denoted as $Q_X \in \mathbb{R}^{N_{axD}}$, with $D$ as the feature dimension. Then we fuse the upstream track query $Q_A$, current position embedding $P_A$ and $Q_X$ together via a temporal-specific MLP:

$$G^t = \text{MLP}_t([Q_A, P_A, Q_X]), \ t=1, \ldots, T_o,$$  

where $[\cdot]$ denotes concatenation. For the scene-level knowledge, the BEV feature $B$ is downscaled to $\psi_l$ resolution for training efficiency to serve as the first block input $F^0$. To further reduce the computational cost, each block follows a downsample-upsample manner with an attention module in between (described below), conducting pixel-agent interaction at $\psi_h$-scaled feature $F^t_{ds}$.

**Pixel-agent interaction.** It is designed to unify the scene- and agent-level understanding when we predict future occupancy. Instead of taking instance-level embeddings as queries and attending to dense features in conventional detection or segmentation transformers, we employ the dense scene feature $F^{t}_{ds}$ as queries, instance-level features as keys and values to update the dense feature over time. Datedlily, we perform self-attention with $F^{t}_{ds}$ to learn a long-range per-pixel interaction, followed by a cross-attention with the agent feature $G^t$. Moreover, to encourage the pixel-agent correspondence, we constrain the cross-attention by an attention mask, which restricts each pixel to only look at the agent occupying it at timestep $t$, inspired by [17]. The update process of the dense feature is formulated as:

$$D^t_{ds} = \text{MHCA}((\text{MHSA}(F^t_{ds}), G^t), \text{atten}_{\text{mask}} = O^t_{vm}).$$  

As the attention mask $O^t_{vm}$ is semantically the same with occupancy, it is also generated via a matrix multiplication between an additional agent-level feature denoted as mask feature $M^t = \text{MLP}(G^t)$ and the dense feature $F^t_{ds}$. After the interaction process in Eq. (7), $D^t_{ds}$ is upsampled to $\psi_l$ size of original BEV. We further add $D^t_{ds}$ with a residual connection from the input $F^{t-1}$ for training stability, and the resultant feature $F^t$ is passed to the next block.

**Instance-level occupancy.** It represents the occupancy with each agent’s identity reserved. It could be simply drawn via matrix multiplication, as in recent query-based segmentation works [18, 46]. Formally, in order to get an occupancy prediction of original size $H \times W$ of BEV feature $B$, all scene-level features $F^t$ are upsampled to $F^t_{dec} \in \mathbb{R}^{C \times H \times W}$ by a convolutional decoder, where $C$ is the channel dimension. For the agent-level feature, we further update the coarse mask feature $M^t$ to the occupancy feature. $U^t \in \mathbb{R}^{N_{axC}}$ by another MLP. We empirically find that generating $U^t$ from mask feature $M^t$ instead of original agent feature $G^t$ leads to better performance. The final instance-level occupancy of timestep $t$ is:

$$\hat{O}^t_A = U^t \cdot F^t_{dec}.$$  

### 2.4. Planning

Planning without HD maps or predefined routes usually requires a high-level command to indicate the direction to go [11, 37]. We also follow this spirit and divide the rough navigation signal into three bins, i.e., turn left, turn right and keep forward. Note that the ego-vehicle query from MotionFormer already encodes ego-vehicle’s feasible behaviors, thus in the planning stage, we further endow it with the command intention, leading to an enhanced “plan query”. It predicts the final trajectory $\hat{\tau}$ by attending to BEV features again for road and traffic information.

To further ensure safety, we introduce an optimization strategy based on Newton’s method during inference:

$$\tau^* = \arg \min_{\tau} f(\tau, \hat{O}),$$  

where $\tau^*$ denotes the ultimate plan, $\hat{O}$ is a classical instance-agnostic occupancy map generated by merging all agents’ predictions, and the target function is calculated by:

$$f(\tau, \hat{O}) = \lambda_{\text{coord}} |\tau, \hat{\tau}|_2 + \lambda_{\text{obs}} \sum_t D(\tau_t, \hat{O}_t),$$  

$$D(\tau_t, \hat{O}_t) = \sum_{|x,y| - \tau_t < d} N(\tau_t - \hat{O}_{x,y}, \sigma).$$  

Here the $l_2$ cost pulls the trajectory toward the original planned goal while the collision term $D$ pushes it away from obstacles on the occupancy map, which is modeled as Gaussian distributions for positions around each waypoint $\tau_t$.

### 2.5. Joint Learning

UniAD is trained in two stages. We first jointly train the tracking and mapping modules for half of training iterations, and then optimize the model end-to-end with all the perception, prediction and planning modules. The two-stage training empirically is found to be more stable. We refer audience to the Supplementary for details of each loss.

**Shared matching policy.** Since UniAD involves instance-wise modeling, pairing predictions to the ground truth set is required in perception and prediction tasks.
Similar to DETR [8, 49], the bipartite matching is adopted in the tracking and online mapping stage. For the tracking task, candidates from newborn queries are paired with ground truth objects through bipartite matching, and predictions from track queries inherit the assigned ground truth index from previous frames. The matching results in the tracking module are further utilized in motion and occupancy tasks as well, not only avoiding repeating operations for each task, but also improving the temporal consistency of per-agent feature from historical tracklet to future motion in the end-to-end framework.

3. Experiments

We conduct experiments on the challenging nuScenes benchmark [6]. Due to space limit, some ablative experiments, visualizations, the full suite of details on metrics and protocols are provided in the Supplementary.

3.1. Main Results

We compare with prior state-of-the-arts, both modularized and end-to-end based approaches. The main metric for each task is marked in gray background in Tables.

Perception results. As for multi-object tracking in Table 2, UniAD yields a significant improvement of +6.5 and +14.2 AMOTA(%) compared to MUTR3D [91] and a prediction-target method ViP3D [30] respectively. Moreover, UniAD achieves the lowest ID switch score showing the temporal consistency for each tracklet. For online mapping in Table 3, UniAD shows excellent ability to segment road elements, especially in lanes (+7.4 IoU(%) compared to BEVFormer) which are crucial for downstream agent-road interaction in motion forecasting. Note that our tracking is slightly inferior to state-of-the-art Immortal Tracker, which is designed by tracking-by-detection paradigm; and the performance on some semantic classes in mapping falls behind c.f. some perception-oriented works. We argue that UniAD is goal-oriented to benefit final planning - not targeting at top-1 performance within single task.

Prediction results. Motion forecasting results are shown in Table 4, where UniAD remarkably outperforms previous vision-based end-to-end methods and reduces errors by 38.3% and 65.4% on minADE compared to PnPNet-vision [50] and ViP3D [30] respectively. In terms of occupancy prediction reported in Table 5, UniAD gets notable advances in nearby areas, yielding +4.0 and +2.0 on IoU-near(%) compared to FIERY [34] and BEVerse [92] with heavy augmentations, respectively.

Planning results. Benefiting from rich spatial-temporal information in both the ego-vehicle query and occupancy, UniAD reduces planning L2 error and collision rate by 51.2% and 56.3% compared to ST-P3 [37], in terms of the average value for the planning horizon. Moreover, it notably outperforms several LiDAR-based counterparts, which is often deemed challenging for perception tasks.

Table 2. Multi-object tracking. UniAD achieves the best results on all metrics over end-to-end MOT methods by a large margin. ↑: Tracking-by-detection (post-association) method.

| Method              | AMOTA↑ | AMOTP↓ | Recall↑ | IDS↓ |
|---------------------|--------|--------|---------|------|
| Immortal Tracker†   | 0.578  | 1.119  | 0.478   | 936  |
| ViP3D [30]          | 0.217  | 1.625  | 0.363   | -    |
| Q3D3T [35]          | 0.242  | 1.518  | 0.399   | -    |
| MUTR3D [91]         | 0.294  | 1.498  | 0.427   | 3822 |
| UniAD               | 0.359  | 1.320  | 0.467   | 960  |

Table 3. Online mapping. UniAD achieves competitive performance with comprehensive road semantics. We report segmentation IoU (%). †: Reimplemented with BEVFormer.

| Method | Lanes↑ | Drivable↑ | Divider↑ | Crossing↑ |
|--------|--------|-----------|----------|-----------|
| VPN [63] | 18.0  | 76.0      | -        | -         |
| LSS [66] | 18.3  | 73.9      | -        | -         |
| BEVFormer [48] | 23.9  | 77.5      | -        | -         |
| BEVerse† [92] | -     | -         | 30.6     | 17.2      |
| UniAD   | 31.3  | 69.1      | 25.7     | 13.8      |

Table 4. Motion forecasting. UniAD remarkably outperforms previous vision-based end-to-end methods (forecasting with image inputs). We also report two settings of modeling vehicles with constant positions or velocities to demonstrate the gain from our approach. †: Reimplemented with BEVFormer.

| Method              | IoU-n.↑ | IoU-f.↑ | VPQ-n.↑ | VPQ-f.↑ |
|---------------------|---------|---------|---------|---------|
| FIERY [34]          | 59.4    | 36.7    | 50.2    | 29.9    |
| StretchBEV [1]      | 55.5    | 37.1    | 46.0    | 29.0    |
| ST-P3 [37]          | -       | 38.9    | -       | 32.1    |
| BEVerse† [92]       | 61.4    | 40.9    | 54.3    | 36.1    |
| UniAD               | 63.4    | 40.2    | 54.7    | 33.5    |

Table 5. Occupancy prediction. UniAD gets significant improvement in nearby areas, which are more critical for planning. "n." and "f." indicates near (30 × 30m) and far (50 × 50m) evaluation ranges respectively. †: Trains with heavy augmentations.

Fig. 3 visualizes the results of all tasks for one complex scene. The ego vehicle drives with notice to the potential movement of a front vehicle and lane. The failure cases of UniAD is summarized in two aspects mainly: (1) inaccurate
results occur in prior modules while the later tasks could still recover, e.g., predictions and planned trajectory remain reasonable though objects have a large heading angle deviation in tracking results; (2) all modules are affected under some long-tail scenarios, e.g., large trucks and trailers.

### 3.2. Ablation Study

**Roadmap toward the ultimate goal.** To validate our goal-oriented design philosophy, we conduct extensive ablations as shown in Table 7 to prove the effectiveness and necessity of preceding modules. To achieve the ultimate goal of planning, we analyze the two types of prediction tasks in our framework. In Exp.10-12, only when motion forecasting and occupancy prediction modules are introduced simultaneously (Exp.12), both metrics of the planning L2 and collision rate achieve the best result, compared to naive end-to-end planning (Exp.10, Fig. 1(c.1)). Thus we conclude that both these two prediction tasks are required for a safe planning objective. Taking a step back, in Exp.7-9, we show the cooperative effect of our two designated types of prediction. The performance of both tasks boosts when they are closely integrated (Exp.9, -3.5% minADE, -5.8% minFDE, -1.3 MR(%) , +2.4 IoU-f., +2.4 VPQ-f.), which demonstrates the necessity to unify these agent- and scene-level representations. Meanwhile, in order to realize a superior motion forecasting performance, we explore how perception modules could contribute in Exp.4-6. Notably, incorporating both tracking and mapping nodes brings remarkable improvement to forecasting results (-9.7% minADE, -12.9% minFDE, -2.3 MR(%)). We also present Exp.1-3, which indicate training perception sub-tasks together leads to comparable results to a single task. Additionally, compared with naive multi-task learning (Exp.0, Fig. 1(b)), our hierarchical design (Exp.12) outperforms it by a significant margin in all essential metrics (-15.2% minADE, -17.0% minFDE, -3.2 MR(%) , +4.9 IoU-f., +5.9 VPQ-f., -0.15m avg.L2, -0.51 avg.Col.(%) ), showing the superiority of our goal-oriented hierarchical design.

**Effect of designs in MotionFormer.** Table 8 shows that all of our proposed components described in Sec. 2.2 contribute to final performance regarding minADE, minFDE, Miss Rate and minFDE-mAP metrics. Notably, the rotated scene-level anchor shows a significant performance boost (-15.8% minADE, -11.2% minFDE, +1.9 minFDE-mAP(%)), indicating that it is essential to do motion forecasting in the scene-centric manner. The agent-goal point interaction enhances the motion query with the goal-oriented visual feature, and surrounding agents can further benefit from considering the ego-vehicle’s intention. Moreover, the non-linear optimization strategy improves the performance (-5.0% minADE, -8.4% minFDE, -1.0 MR(%) , +0.7 minFDE-mAP(%)) by taking perceptual uncertainty into account in the end-to-end scenario.

**Effect of designs in OccFormer.** As illustrated in Table 9, attending each pixel to all agents without locality constraints (Exp.2) results in slightly worse performance compared to an attention-free baseline. The occupancy-guided attention mask resolves the problem and brings in gain, especially for nearby areas (Exp.3, +1.0 IoU-n, +1.4 VPQ-n.). Additionally, reusing mask feature $M_t$ instead of the agent feature to acquire the occupancy feature further enhances performance.

**Effect of designs in Planner.** We provide ablations on the proposed designs in planner in Table 10, i.e., attending BEV features, training with the collision loss and the optimization strategy with occupancy. The collision rate is reduced with all parts applied, which is essential for safety.

**Model complexity and Computational cost.** We measure the complexity of UniAD and runtime on an Nvidia Tesla A100 GPU, as depicted in Table 11. Though the decoder part of tasks brings a certain amount of parameters, the computational complexity mainly comes from the encoder part, compared to the original BEVFormer detector (ID. 1). We also provide comparison with the recent BEVERse [92]. UniAD owns more tasks, achieves superior performance, and has lower FLOPs - indicating affordable budget to additional computation cost.

### 4. Conclusion and Future Work

We discuss the system-level design for the autonomous driving algorithm framework. A hierarchical, goal-oriented pipeline is proposed toward the ultimate pursuit for planning, namely UniAD. We provide detailed analysis on the necessity of each module within perception and prediction. To unify tasks, a query-based design is proposed to connect all nodes in UniAD, benefiting from richer representations for agent interaction in the environment. Extensive experiments verify the proposed method in all aspects.

**Limitations and future work.** Coordinating such a comprehensive system with multiple tasks is non-trivial and needs extensive computational power, especially trained
### Table 7. Detailed ablations on the effectiveness of each task.

Only main metrics are shown for brevity. We can conclude that two perception sub-tasks greatly help motion forecasting, and prediction performance also benefits from unifying the two prediction modules. With all prior representations, our goal-planning boosts significantly to ensure the safety. UniAD outperforms naive MTL solution by a large margin for prediction and planning tasks, and it also owns the superiority that no substantial perceptual performance drop occurs. “avg.L2” and “avg.Col.” are the average values across the planning horizon. ∗: ID-0 is the MTL scheme with separate heads for each task.

### Table 8. Ablation for designs in the motion forecasting module.

All components contribute to the ultimate performance. “Scene-l. Anch.” denotes rotated scene-level anchors. “Goal Inter.” means the agent-goal point interaction. “Ego Q” represents the ego-vehicle query and “NLO.” is the non-linear optimization strategy. ∗: a metric considering detection and forecasting accuracy simultaneously (details in the Supplementary).

### Table 9. Ablation for designs in the occupancy prediction module.

Cross-attention with masks and the reuse of mask feature helps improve the prediction. “Cross. Attn.” and “Attn. Mask” represents cross-attention and the attention mask in the pixel-agent interaction respectively. “Mask Feat.” denotes the reuse of mask feature for instance-level occupancy.

### References

[1] Adil Kaan Akan and Fatma Güney. StretchBEV: Stretching future instance prediction spatially and temporally. In ECCV, 2022. 6, 14

[2] Mayank Bansal, Alex Krizhevsky, and Abhijit Ogale. ChauffeurNet: Learning to drive by imitating the best and synthesizing the worst. arXiv preprint
Table 10. Ablation for designs in the planning module. Results demonstrate the necessity of each preceding task. “BEV Att.” indicates attending to BEV feature. “Col. Loss” denotes collision loss. “Occ. Optim.” is the optimization strategy with occupancy.

| ID | BEV Att | Col. Loss | Occ. Optim. | L2 | 1s  | 2s  | 3s  | Col. Rate |
|----|---------|-----------|-------------|----|-----|-----|-----|----------|
| 1  | ✓       | ✓         | ✓           | 0.44 | 0.36 | 0.88 | 1.64 |
| 2  | ✓       | ✓         | ✓           | 0.44 | 0.35 | 0.71 | 1.58 |
| 3  | ✓       | ✓         | ✓           | 0.44 | 0.30 | 0.51 | 1.39 |
| 4  | ✓ ✓     | ✓ ✓       | ✓ ✓         | 0.44 | 0.54 | 1.09 | 1.81 |

Table 11. Computational complexity and runtime with different modules incorporated. ID.1 is similar to original BEVFormer [48], and ID. 0 (BEVerse-Tiny) [92] is an MTL framework.

| ID | Det. Track | Map | Motion | Occ. Plan | #Params | FLOPs | FPS |
|----|------------|-----|--------|-----------|---------|-------|-----|
| 0  | [92]       | ✓   | ✓      | ✓         | 102.5M  | 1921G |     |
| 1  | ✓          | ✓   | ✓      | ✓         | 65.9M   | 1324G | 2.7 |
| 2  | ✓          | ✓   | ✓      | ✓         | 68.2M   | 1326G | 2.73|
| 3  | ✓          | ✓   | ✓      | ✓         | 95.8M   | 1520G | 2.2 |
| 4  | ✓          | ✓   | ✓      | ✓         | 108.6M  | 1535G | 2.1 |
| 5  | ✓          | ✓   | ✓      | ✓         | 122.5M  | 1709G | 2.0 |
| 6  | ✓          | ✓   | ✓      | ✓         | 125.0M  | 1709G | 1.8 |

arXiv:1812.03079, 2018. 15

[3] Hans Georg Bock and Karl-Josef Plitt. A multiple shooting algorithm for direct solution of optimal control problems. IFAC Proceedings Volumes, 1984. 4

[4] Mariusz Bojarski, Davide Del Testa, Daniel Dworakowski, Bernhard Firner, Beat Flepp, Prasoon Goyal, Lawrence D Jackel, Mathew Monfort, Urs Muller, Jiakai Zhang, Xin Zhang, Jake Zhao, and Zieba Karol. End to end learning for self-driving cars. arXiv preprint arXiv:1604.07316, 2016. 15

[5] Thibault Buhet, Émilie Wirbel, and Xavier Perrotton. PLOP: Probabilistic objects trajectory planning for autonomous driving. In CoRL, 2020. 15

[6] Holger Caesar, Varun Bankiti, Alex H Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A multimodal dataset for autonomous driving. In CVPR, 2020. 6

[7] Holger Caesar, Juraj Kabzan, Kok Seang Tan, Whye Kit Fong, Eric Wolff, Alex Lang, Luke Fletcher, Oscar Beijbom, and Sammy Omari. nuplan: A closed-loop ml-based planning benchmark for autonomous vehicles. arXiv preprint arXiv:2106.11810, 2021. 4

[8] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In ECCV, 2020. 3, 6, 14, 15, 17

[9] Sergio Casas, Cole Gulino, Renjie Liao, and Raquel Urtasun. Spagnn: Spatially-aware graph neural net-works for relational behavior forecasting from sensor data. In ICRA, 2020. 14

[10] Sergio Casas, Wenjie Luo, and Raquel Urtasun. Intentnet: Learning to predict intention from raw sensor data. In CoRL, 2018. 14

[11] Sergio Casas, Abbas Sadat, and Raquel Urtasun. Mp3: A unified model to map, perceive, predict and plan. In CVPR, 2021. 2, 5, 14, 15

[12] Yuning Chai, Benjamin Sapp, Mayank Bansal, and Dragomir Anguelov. Multipath: Multiple probabilistic anchor trajectory hypotheses for behavior prediction. In CoRL, 2020. 14, 19

[13] Raphael Chekroun, Marin Toromanoff, Sascha Hornauer, and Fabien Moutarde. GRI: General reinforced imitation and its application to vision-based autonomous driving. arXiv preprint 2111.08575, 2021. 15

[14] Dian Chen, Vladlen Koltun, and Philipp Krähenbühl. Learning to drive from a world on rails. In ICCV, 2021. 2, 15

[15] Dian Chen and Philipp Krähenbühl. Learning from all vehicles. In CVPR, 2022. 2, 15

[16] Dian Chen, Brady Zhou, Vladlen Koltun, and Philipp Krähenbühl. Learning by cheating. In CoRL, 2020. 2, 15

[17] Bowen Cheng, Ishan Misra, Alexander G. Schwing, Alexander Kirillov, and Rohit Giridhar. Masked-attention mask transformer for universal image segmentation. In CVPR, 2022. 5

[18] Bowen Cheng, Alex Schwing, and Alexander Kirillov. Per-pixel classification is not all you need for semantic segmentation. In NeurIPS, 2021. 5

[19] Kashyap Chitta, Aditya Prakash, and Andreas Geiger. NEAT: Neural attention fields for end-to-end autonomous driving. In ICCV, 2021. 2, 15

[20] Kashyap Chitta, Aditya Prakash, Bernhard Jaeger, Ze-hao Yu, Katrin Renz, and Andreas Geiger. Transfuser: Imitation with transformer-based sensor fusion for autonomous driving. IEEE TPAMI, 2022. 2, 15

[21] Felipe Codevilla, Matthias Müller, Antonio López, Vladlen Koltun, and Alexey Dosovitskiy. End-to-end driving via conditional imitation learning. In ICRA, 2018. 2, 15

[22] Felipe Codevilla, Eder Santana, Antonio M López, and Adrien Gaidon. Exploring the limitations of behavior cloning for autonomous driving. In ICCV, 2019. 2, 15

[23] Michael Crawshaw. Multi-task learning with deep neural networks: A survey. arXiv preprint arXiv:2009.09796, 2020. 2
[24] Alexander Cui, Sergio Casas, Abbas Sadat, Renjie Liao, and Raquel Urtasun. Lookout: Diverse multi-future prediction and planning for self-driving. In ICCV, 2021. 15

[25] Nemanja Djuric, Henggang Cui, Zhaosen Su, Shangxuan Wu, Huahua Wang, Fang-Chieh Chou, Luisa San Martin, Song Feng, Rui Hu, Yang Xu, Alyssa Dayan, Sidney Zhang, Brian C. Becker, Gregory P. Meyer, Carlos Vallespi-Gonzalez, and Carl K. Wellington. Multixnet: Multiclass multistage multimodal motion prediction. In IV, 2021. 14

[26] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. CARLA: An open urban driving simulator. In CoRL, 2017. 2

[27] Scott Ettinger, Shuyang Cheng, Benjamin Caine, Chenxi Liu, Hang Zhao, Sabeek Pradhan, Yuning Chai, Ben Sapp, Charles R Qi, Yin Zhou, Zoey Yang, Aurélien Chouard, Pei Sun, Jiquan Ngiam, Vijay Vasudevan, Alexander McCauley, Jonathon Shlens, and Dragomir Anguelov. Large scale interactive motion forecasting for autonomous driving: The waymo open motion dataset. In ICCV, 2021. 13

[28] Sudeep Fadadu, Shreyash Pandey, Darshan Hegde, Yi Shi, Fang-Chieh Chou, Nemanja Djuric, and Carlos Vallespi-Gonzalez. Multi-view fusion of sensor data for improved perception and prediction in autonomous driving. In WACV, 2022. 14

[29] Jiyang Gao, Chen Sun, Hang Zhao, Yi Shen, Dragomir Anguelov, Congcong Li, and Cordelia Schmid. Vectornet: Encoding hd maps and agent dynamics from vectorized representation. In CVPR, 2020. 14

[30] Junru Gu, Chenxu Hu, Tianyuan Zhang, Xuanxao Chen, Yilun Wang, Yue Wang, and Hang Zhao. ViP3D: End-to-end visual trajectory prediction via 3d agent queries. arXiv preprint arXiv:2208.01582, 2022. 2, 6, 14, 20

[31] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016. 20

[32] Noureldin Hendy, Cooper Sloan, Feng Tian, Pengfei Duan, Nick Charchut, Yuesong Xie, Chuang Wang, and James Philbin. Fishing net: Future inference of semantic heatmaps in grids. arXiv preprint arXiv:2006.09917, 2020. 14

[33] Anthony Hu, Gianluca Corrado, Nicolas Griffiths, Zak Murez, Corina Gurau, Hudson Yeo, Alex Kendall, Roberto Cipolla, and Jamie Shotton. Model-based imitation learning for urban driving. In NeurIPS, 2022. 15

[34] Anthony Hu, Zak Murez, Nikhil Mohan, Sofia Dudas, Jeffrey Hawke, Vijay Badrinarayanan, Roberto Cipolla, and Alex Kendall. FIERY: Future instance prediction in bird’s-eye view from surround monocular cameras. In ICCV, 2021. 4, 6, 14, 20

[35] Hou-Ning Hu, Yung-Hsu Yang, Tobias Fischer, Trevor Darrell, Fisher Yu, and Min Sun. Monocular quasi-dense 3d object tracking. IEEE TPAMI, 2022. 6

[36] Hou-Ning Hu, Yung-Hsu Yang, Tobias Fischer, Trevor Darrell, Fisher Yu, and Min Sun. Monocular quasi-dense 3d object tracking. IEEE TPAMI, 2022. 6

[37] Hou-Ning Hu, Yung-Hsu Yang, Tobias Fischer, Trevor Darrell, Fisher Yu, and Min Sun. Monocular quasi-dense 3d object tracking. IEEE TPAMI, 2022. 6

[38] Zhiyu Huang, Haochen Liu, Jingda Wu, and Chen Lv. Differentiable integrated motion prediction and planning with learnable cost function for autonomous driving. arXiv preprint arXiv:2207.10422, 2022. 14

[39] Boris Ivanovic, Amine Elhafsi, Guy Rosman, Adrien Gaidon, and Marco Pavone. MATS: An interpretable trajectory forecasting representation for planning and control. In CoRL, 2021. 14

[40] Alexey Kamenev, Lirui Wang, Ollin Boer Bohan, Ishwar Kulkarni, Bilal Kartal, Artem Molchanov, Stan Birchfield, David Nister, and Nikolai Smolyanskiy. Predictionnet: Real-time joint probabilistic traffic prediction for planning, control, and simulation. In ICRA, 2022. 14

[41] Alex Kendall, Jeffrey Hawke, David Janz, Przemyslaw Mazur, Daniele Reda, John-Mark Allen, Vinh-Dieu Lam, Alex Bewley, and Amar Shah. Learning to drive in a day. In I CRA, 2019. 15

[42] Tarasha Khurana, Peiyun Hu, Achal Dave, Jason Ziglar, David Held, and Deva Ramanan. Differentiable raycasting for self-supervised occupancy forecasting. In ECCV, 2022. 7, 15

[43] Dahun Kim, Sanghyun Woo, Joon-Young Lee, and In So Kweon. Video panoptic segmentation. In CVPR, 2020. 20

[44] Jinkyu Kim, Reza Mahjourian, Scott Ettinger, Mayank Bansal, Brandyn White, Ben Sapp, and Dragomir Anguelov. Stopnet: Scalable trajectory and occupancy prediction for urban autonomous driving. arXiv preprint arXiv:2206.09991, 2022. 3

[45] Youngwan Lee, Joong-won Hwang, Sangrok Lee, Yuseok Bae, and Jongyoul Park. An energy and gpu-computation efficient backbone network for real-time object detection. In CVPRW, 2019. 20
[46] Feng Li, Hao Zhang, Shilong Liu, Lei Zhang, Lionel M Ni, and Heung-Yeung Shum. Mask dino: Towards a unified transformer-based framework for object detection and segmentation. *arXiv preprint arXiv:2206.02777*, 2022. 5

[47] Lingyun Luke Li, Bin Yang, Ming Liang, Wenyuan Zeng, Mengye Ren, Sean Segal, and Raquel Urtasun. End-to-end contextual perception and prediction with interaction transformer. In *IROS*, 2020. 14

[48] Zhiqi Li, Wenhai Wang, Hongyang Li, Enze Xie, Chonghao Sima, Tong Lu, Qiao Yu, and Jifeng Dai. BEVFormer: Learning bird’s-eye-view representation from multi-camera images via spatiotemporal transformers. In *ECCV*, 2022. 2, 6, 9, 15, 19

[49] Zhiqi Li, Wenhai Wang, Enze Xie, Zhiding Yu, Anima Anandkumar, Jose M Alvarez, Ping Luo, and Tong Lu. Panoptic segformer: Delving deeper into panoptic segmentation with transformers. In *CVPR*, 2022. 3, 6, 15, 19

[50] Ming Liang, Bin Yang, Wenyuan Zeng, Yun Chen, Rui Hu, Sergio Casas, and Raquel Urtasun. Pnpnet: End-to-end perception and prediction with tracking in the loop. In *CVPR*, 2020. 1, 2, 6, 14, 20

[51] Xiaodan Liang, Tairui Wang, Luona Yang, and Eric Xing. Cirl: Controllable imitative reinforcement learning for vision-based self-driving. In *ECCV*, 2018. 15

[52] Xiwen Liang, Yangxin Wu, Jianhua Han, Hang Xu, Chunjing Xu, and Xiaodan Liang. Effective adaptation in multi-task co-training for unified autonomous driving. In *NeurIPS*, 2022. 2

[53] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *ICCV*, 2017. 19

[54] Jerry Liu, Wenyuan Zeng, Raquel Urtasun, and Ersin Yumer. Deep structured reactive planning. In *ICRA*, 2021. 14

[55] Yicheng Liu, Jinghui Zhang, Liangji Fang, Qinhong Jiang, and Bolei Zhou. Multimodal motion prediction with stacked transformers. In *CVPR*, 2021. 3

[56] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *ICLR*, 2018. 19

[57] Wenjie Luo, Bin Yang, and Raquel Urtasun. Fast and furious: Real time end-to-end 3d detection, tracking and motion forecasting with a single convolutional net. In *CVPR*, 2018. 1, 14, 20

[58] Fausto Milletari, Nassir Navab, and Seyed-Ahmad Ahmadi. V-net: Fully convolutional neural networks for volumetric medical image segmentation. In *3DV*, 2016. 19

[59] Mobileye. Mobileye under the hood. [https://www.mobileye.com/ces-2022/](https://www.mobileye.com/ces-2022/), 2022. 1, 2

[60] Nigamaa Nayakanti, Rami Al-Rfou, Aurick Zhou, Kratarth Goel, Khaled S Refaat, and Benjamin Sapp. Wayformer: Motion forecasting via simple & efficient attention networks. *arXiv preprint arXiv:2207.05844*, 2022. 3

[61] Jiqian Ngiam, Benjamin Caine, Vijay Vasudevan, Zhengdong Zhang, Hao-Tien Lewis Chiang, Jeffrey Ling, Rebecca Roelofs, Alex Bewley, Chenxi Liu, Ashish Vemugopal, David Weiss, Ben Sapp, Zhifeng Chen, and Jonathon Shlens. Scene transformer: A unified multi-task model for behavior prediction and planning. In *ICLR*, 2022. 3, 14

[62] Nvidia. NVIDIA DRIVE End-to-End Solutions for Autonomous Vehicles. [https://developer.nvidia.com/drive](https://developer.nvidia.com/drive), 2022. 1, 2

[63] Bowen Pan, Jiankai Sun, Ho Yin Tiga Leung, Alex Andonian, and Bolei Zhou. Cross-view semantic segmentation for sensing surroundings. *IEEE RA-L*, 2020. 6

[64] Dennis Park, Rares Ambrus, Vitor Guizilini, Jie Li, and Adrien Gaidon. Is pseudo-lidar needed for monocular 3d object detection? In *ICCV*, 2021. 21

[65] Neelhar Peri, Jonathon Luiten, Mengtian Li, Aljoša Ošep, Laura Leal-Taixé, and Deva Ramanan. Forecasting from lidar via future object detection. In *CVPR*, 2022. 14, 20

[66] Jonah Philion and Sanja Fidler. Lift, splat, shoot: Encoding images from arbitrary camera rigs by implicitly unprojecting to 3d. In *ECCV*, 2020. 6

[67] Dean A Pomerleau. Alvinn: An autonomous land vehicle in a neural network. In *NeurIPS*, 1988. 15

[68] Aditya Prakash, Kashyap Chitta, and Andreas Geiger. Multi-modal fusion transformer for end-to-end autonomous driving. In *CVPR*, 2021. 2, 15

[69] Scott Reed, Konrad Zolna, Emilio Parisotto, Sergio Gomez Colmenarejo, Alexander Novikov, Gabriel Barth-Maron, Mai Gimenez, Yury Sutsky, Jackie Kay, Jost Tobias Springenberg, Tom Eccles, Jake Bruce, Ali Razavi, Ashley Edwards, Nicolas Heess, Yutian Chen, Raia Hadsell, Oriol Vinyals, Mahyar Bordbar, and Nando de Freitas. A generalist agent. *arXiv preprint arXiv:2205.06175*, 2022. 1

[70] Hamid Rezatofighi, Nathan Tsoi, JunYoung Gwak, Amir Sadeghian, Ian Reid, and Silvio Savarese. Generalized intersection over union: A metric and a loss for bounding box regression. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 658–666, 2019. 19
Nicholas Rhinehart, Rowan McAllister, Kris Kitani, and Sergey Levine. PRECOG: Prediction conditioned on goals in visual multi-agent settings. In ICCV, 2019.

Abbas Sadat, Sergio Casas, Mengye Ren, Xinyu Wu, Pranaab Dhawan, and Raquel Urtasun. Perceive, predict, and plan: Safe motion planning through interpretable semantic representations. In ECCV, 2020.

Hao Shao, Letian Wang, Ruobing Chen, Hongsheng Li, and Yu Liu. Safety-enhanced autonomous driving using interpretable sensor fusion transformer. In CoRL, 2022.

Shaoshuai Shi, Li Jiang, Dengxin Dai, and Bernt Schiele. Motion transformer with global intention localization and local movement refinement. In NeurIPS, 2022.

Hao Shao, Letian Wang, Ruobing Chen, Hongsheng Li, and Yu Liu. Safety-enhanced autonomous driving using interpretable sensor fusion transformer. In CoRL, 2022.

Shaoshuai Shi, Li Jiang, Dengxin Dai, and Bernt Schiele. Motion transformer with global intention localization and local movement refinement. In NeurIPS, 2022.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NeurIPS, 2017.

Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai, Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. Ofa: Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework. In ICML, 2022.

Qitai Wang, Yuntao Chen, Ziqi Pang, Naiyan Wang, and Zhaoxiang Zhang. Immortal tracker: Tracklet never dies. arXiv preprint arXiv:2111.13672, 2021.

Bob Wei, Mengye Ren, Wenyuan Zeng, Ming Liang, Bin Yang, and Raquel Urtasun. Perceive, attend, and drive: Learning spatial attention for safe self-driving. In ICRA, 2021.

Pengxiang Wu, SiHeng Chen, and Dimitris N Metaxas. Motionnet: Joint perception and motion prediction for autonomous driving based on bird’s eye view maps. In CVPR, 2020.

Penghao Wu, Xiaosong Jia, Li Chen, Junchi Yan, Hongyang Li, and Yu Qiao. Trajectory-guided control prediction for end-to-end autonomous driving: A simple yet strong baseline. In NeurIPS, 2022.

Ye Yuan, Xinshuo Weng, Yanglan Ou, and Kris M Kitani. Agentformer: Agent-aware transformers for socio-temporal multi-agent forecasting. In ICCV, 2021.

Fangao Zeng, Bin Dong, Tiancai Wang, Xiangyu Zhang, and Yichen Wei. Motr: End-to-end multiple-object tracking with transformer. In ECCV, 2021.

Wenyuan Zeng, Wenjie Luo, Simon Suo, Abbas Sadat, Bin Yang, Sergio Casas, and Raquel Urtasun. End-to-end interpretable neural motion planner. In CVPR, 2019.

Wenyuan Zeng, Shenlong Wang, Renjie Liao, Yun Chen, Bin Yang, and Raquel Urtasun. Dsdnet: Deep structured self-driving network. In ECCV, 2020.

Jimuyang Zhang and Eshed Ohn-Bar. Learning by watching. In CVPR, 2021.

Tianyuan Zhang, Xuanxao Chen, Yue Wang, Yilun Wang, and Hang Zhao. MUTR3D: A Multi-camera Tracking Framework via 3D-to-2D Queries. In CVPR Workshop, 2022.

Yunpeng Zhang, Zheng Zhu, Wenzhao Zheng, Junjie Huang, Guan Huang, Jie Zhou, and Jiwen Lu. BEVerse: Unified perception and prediction in birds-eye-view for vision-centric autonomous driving. arXiv preprint arXiv:2205.09743, 2022.

Zhejun Zhang, Alexander Liniger, Dengxin Dai, Fisher Yu, and Luc Van Gool. End-to-end urban driving by imitating a reinforcement learning coach. In ICCV, 2021.

Hang Zhao, Jiyang Gao, Tian Lan, Chen Sun, Benjamin Sapp, Balakrishnan Varadarajan, Yue Shen, Yi Shen, Yuning Chai, Cordelia Schmid, Congcong Li, and Dragomir Anguelov. TTN: Target-driven trajectory prediction. In CoRL, 2020.
warded to the motion module. Additionally, note that we
each frame, and their corresponding features
cess. The final output is a series of associated 3D boxes in
indicating whether it is occupied, and occupancy prediction
future understanding. For the 
query for down-
scene evolves with sparse agent knowledge, our proposed
BEV map. Similar to $Q_A$, the map queries $Q_M$ would be
further utilized in the motion forecasting module to model
ego-vehicle accordingly.

Online mapping. Map intuitively embodies the geometric
and semantic information of the environment, and online
mapping is to segment meaningful road elements with on-
board sensor data (multi-view images in our case) as a sub-
stitute for offline annotated HD maps. In UniAD, we model
the online map into four categories: lanes, drivable area, di-
viders and pedestrian crossings, and we segment them in the
BEV map. Similar to $Q_A$, the map queries $Q_M$ would be
further utilized in the motion forecasting module to model
the agent-map interaction.

Motion forecasting. Bridging perception and planning,
prediction plays an important role in the whole autonomous
driving system to ensure final safety. Typically, motion
 forecasting is an independently developed module that pre-
dicts agents’ future trajectories with detected bounding
boxes and HD maps. And the bounding boxes are ground
truth annotations in most current motion datasets [27],
which is not realistic in onboard scenarios. While in this
paper, the motion forecasting module takes previously en-
coded sparse queries (i.e., $Q_A$ and $Q_M$) and dense BEV fea-
tures $B$ as inputs, and forecasts $K$ plausible trajectories in
future $T$ timesteps for each agent. Besides, to be compatible
with our end-to-end and scene-centric scenarios, we predict
trajectories as offset according to each agent’s current po-
sitions. The agent features before the last decoding MLPS,
which have encoded both the historical and future informa-
tion will be sent to the occupancy module for scene-level
future understanding. For the ego-vehicle query, it predicts
future ego-motion as well (actually providing a coarse plan-
ing estimation), and the feature is employed by the planner
to generate the ultimate goal.

Occupancy prediction. Occupancy grid map is a dis-
cretized BEV representation where each cell holds a belief
indicating whether it is occupied, and occupancy prediction
task is designed to discover how the grid map changes in
the future for $T_o$ timesteps with multiple agent dynamics.
Complementary to motion forecasting which is conditioned
on sparse agents, occupancy prediction is densely repre-
resented in the whole-scene level. To investigate how the
scene evolves with sparse agent knowledge, our proposed
occupancy module takes as inputs both the observed BEV
feature $B$ and agent features $G_o$. After the multi-step agent-
scene interaction (detailedly described in Appendix E), the
instance-level probability map $\hat{O}_A \in \mathbb{R}^{N_o \times H_o \times W_o}$ is gen-
erated via matrix multiplication between occupancy feature
and dense scene feature. To form whole-scene occupancy

Dai. Uni-perceiver-moe: Learning sparse generalist
models with conditional moes. In NeurIPS, 2022. 1

[96] Xizhou Zhu, Weijie Su, Lewei Lu, Bin Li, Xiaogang
Wang, and Jifeng Dai. Deformable detr: Deformable
transformers for end-to-end object detection. In ICLR,
2020. 3, 4, 15, 17
with agent identity preserved $\hat{O}^t \in \mathbb{R}^{H \times W}$ which is used for occupancy evaluation and downstream planning, we simply merge the instance-level probability at each timestep using pixel-wise argmax as in [8].

Planning. As an ultimate goal, the planning module takes all upstream results into consideration. Traditional planning methods in the industry often are rule-based, formulated by “if-else” state machines conditioned on various scenarios which are described with prior detection and prediction results. In our learning-based model, we take the upstream ego-vehicle query, and the dense BEV feature $B$ as input, and predict one trajectory $\hat{\tau}$ for total $T_p$ timesteps. Then, the trajectory $\hat{\tau}$ is optimized with the upstream predicted future occupancy $\hat{O}$ to avoid collision and ensure final safety.

B. The Necessity of Each Task

In terms of perception, tracking in the loop as does in PnPNet [50] and ViP3D [30] is proven to complement spatial-temporal features and provide history tracks for occluded agents, refraining from catastrophic decisions for downstream planning. With the aid of high-definition (HD) maps [30, 50, 72, 88] and motion forecasting, planning become more accurate toward higher-level intelligence. However, such information is expensive to construct and prone to be outdated, raising the demand for online mapping without HD maps. As for prediction, motion forecasting [10, 29, 50, 94] generates long-term future behaviors and preserves agent identity in form of sparse waypoint outputs. Nonetheless, there exists the challenge to integrate non-differentiable box representation into subsequent planning module [30, 50]. Some recent literature investigates another type of prediction task named as occupancy [77] prediction to assist end-to-end planning, in form of cost map. However, the lack of agent identity and dynamics in occupancy makes it impractical to model social interactions for safe planning. The large computational consumption of modeling multi-step dense features also leads to a much shorter temporal horizon compared to motion forecasting. Therefore, to benefit from the two complementary types of prediction tasks for safe planning, we incorporate both agent-centric motion and whole-scene occupancy in UniAD.

C. Related Work

C.1. Joint perception and prediction

Joint learning of perception and prediction is proposed to avoid the cascading error in traditional modular-independence pipelines. Similar to the motion forecasting task alone, it usually has two types of output representations: agent-level bounding boxes and scene-level occupancy grid maps. Pioneering work FaF [57] predicts boxes in the future and aggregates past information to produce tracklets. [10] extends it to reason about intentions and [25, 28] further predict future states in a refinement fashion. Some exploit detection first and utilize agent features in the second prediction stage [9, 47, 65]. Note that history information is ignored, PnPNet [50] enriches it by estimating tracking association scores to avert the non-differentiable optimization process. Yet, all these methods rely on non-maximum suppression (NMS) in detection which still leads to information loss. ViP3D [30] which is closely related to our work, employs agent queries in [91] to forecasting, taking HD map as another input. We follow the philosophy of [30, 91] in agent track queries, but also develop non-linear optimization on target trajectories to alleviate the potential inaccurate perception problem. Moreover, we introduce an ego-vehicle query for better capturing the ego behaviors in the dynamic environment, and incorporate online mapping to prevent the localization risk or high construction cost with HD map.

The alternative representation, namely the occupancy grid map, discretizes the BEV map into grid cells which hold a belief indicating if it is occupied. Wu et al. [84] estimates a dense motion field, while it could not capture multi-modal behaviors. Fishing Net [32] also predicts deterministic future BEV semantic segmentation with multiple sensors. To address this, [72] proposes non-parametric distribution of future semantic occupancy and FIERY [34] devises the first paradigm for multi-view cameras. A few methods improve the performance of FIERY with more sophisticated uncertainty modeling [1, 37, 92]. Notably, this representation could easily extend to motion planning for collision avoidance [11, 37, 72], while it loses the agent identity characteristic and takes a heavy burden to computation which may constrain the prediction horizon. In contrast, we leverage agent-level information to occupancy prediction and ensure accurate and safe planning through unifying these two modes.

C.2. Joint prediction and planning

PRECOG [71] proposes a recurrent model that conditions forecasting on the goal position of the ego vehicle, while PiP [75] generates agents’ motion considering complete presumed planning trajectories. However, producing a rough future trajectory is still challenging in the real world, toward which [34] presents a deep structured model to derive both prediction and planning from the same set of learnable costs. [38, 39] couple the prediction model with classic optimization methods. Meanwhile, some motion forecasting methods implicitly include the planning task by producing their future trajectories simultaneously [12, 40, 61]. Similarly, we encode possible behaviors of ego vehicle in the scene-centric motion forecasting module, but the interpretable occupancy map is utilized to further optimize the
plan to stay safe.

C.3. End-to-end motion planning

End-to-end motion planning has been an active research domain since Pomerleau [67] uses a single neural network that directly predicts control signals. Subsequent studies make great advances especially in closed-loop simulation with deeper networks [4], multi-modal inputs [2, 21, 68], multi-task learning [20, 85], reinforcement learning [13, 14, 41, 51, 78] and distillation from certain privileged knowledge [16, 90, 93]. However, for such methods of directly generating control outputs from sensor data, the transfer from synthetic environment to realistic application remains a problem considering their robustness and safety assurance [22, 37]. Thus researchers aim at explicitly designing the intermediate representations of the network to prompt safety, where predicting how the scene evolves attracts broad interest. Some works [19, 33, 73] jointly decode planning and BEV semantic predictions to enhance interpretability, while PLOP [5] adopts a polynomial formulation to provide smooth planning results for both ego vehicle and neighbors. Cui et al. [24] introduces a contingency planner with diverse set of future predictions and LAV [15] trains the planner with all vehicles’ trajectories to provide richer training data. NMP [88] and its variant [83] estimate a cost volume to select the plan with minimal cost besides deterministic future perception. Though they risk producing inconsistent results between two modules, the cost map design is intuitive to recover the final plan in complex scenarios. Inspired by [88], most recent works [11, 36, 37, 72, 89] propose models that construct costs with both learned occupancy prediction and hand-crafted penalties. However, their performances heavily rely on the tailored cost based on human experience and the distribution from where trajectories are sampled [42]. Contrary to these approaches, we leverage the ego-motion information without sophisticated cost design and present the first attempt that incorporates the tracking module along with two genres of prediction representations simultaneously in an end-to-end model.

D. Notations

We provide a lookup table of notations and their shapes mentioned in this paper in Table 12 for reference.

E. Implementation Details

E.1. Detection and Tracking

We inherit most of the detection designs from BEVFormer [48] which takes a BEV encoder to transform image features into BEV feature $B$ and adopts a Deformable DETR head [96] to perform detection on $B$. To further conduct end-to-end tracking without heavy post association, we introduce another group of queries named track queries as in MOTR [87] which continuously tracks previously observed instances according to its assigned track ID. We introduce the tracking process in detail below.

Training stage: At the beginning (i.e., first frame) of each training sequence, all queries are considered detection queries and predict all newborn objects, which is actually the same as BEVFormer. Detection queries are matched to the ground truth by the Hungarian algorithm [8]. They will be stored and updated via the query interaction module (QIM) for the next timestamp serving as track queries following MOTR [87]. In the next timestamp, track queries will be directly matched with a part of ground-truth objects according to the corresponding track ID, and detection queries will be matched with the remaining ground-truth objects (newborn objects). To stabilize training, we adopt the 3D IoU metric to filter the matched queries. Only those predictions having the 3D IoU with ground-truth boxes larger than a certain threshold (0.5 in practice) will be stored and updated.

Inference stage: Different from the training stage, each frame of a sequence is sent to the network sequentially, meaning that track queries could exist for a longer horizon than the training time. Another difference emerging in the inference stage is about query updating, that we use classification scores to filter the queries (0.4 for detection queries and 0.35 for track queries in practice) instead of the 3D IoU metric since the ground truth is not available. Besides, to avoid the interruption of tracklets caused by short-time occlusion, we use a lifecycle mechanism for the tracklets in the inference stage. Specifically, for each track query, it will be considered to disappear completely and be removed only when its corresponding classification score is smaller than 0.35 for a continuous period (2s in practice).

E.2. Online Mapping

Following [49], we decompose the map query set into thing queries and stuff queries. The thing queries model instance-wise map elements (i.e., lanes, boundaries, and pedestrian crossings) and are matched with ground truth via bipartite matching, while the stuff query is only in charge of semantic elements (i.e., drivable area) and is processed with a class-fixed assignment. We set the total number of thing queries to 300 and only 1 stuff query for the drivable area. Also, we stack 6 location decoder layers and 4 mask decoder layers (we follow the structure of those layers as in [49]). We empirically choose thing queries after the location decoder as our map queries $Q_M$ for downstream tasks.

E.3. Motion Forecasting

To better illustrate the details, we provide a diagram as shown in Fig. 4. Our MotionFormer takes $I_0^n, I_T^n, \hat{x}_0, x_{T-1}^l \in \mathbb{R}^{K \times 2}$ to embed query position, and takes $O^{t-1}\text{ctx}$ as query context. Specifically, the anchors are clustered among
| Notation | Shape & Params. | Description |
|----------|-----------------|-------------|
| $Q_o$    | 900             | number of initial object queries |
| $D$      | 256             | embed dimensions |
| $B$      | $200 \times 200 \times 256$ | BEV feature encoded by a multi-view framework |
| $N$      | 6               | number of transformer decoder layers for TrackFormer |
| $N$      | 6               | number of transformer decoder layers and for MapFormer |
| $N$      | 4               | number of mask decoder layers and for MapFormer |
| $N$      | 3               | number of transformer decoder layers for MotionFormer |
| $N$      | 5               | number of transformer decoder layers for OccFormer |
| $N$      | 3               | number of transformer decoder layers for Planner |
| $N_a$    | $\text{dynamic}$ | number of agents from TrackFormer |
| $N_m$    | 300             | number of map queries from MapFormer |
| $Q_A$    | $N_a \times 256$ | agent features from TrackFormer |
| $P_A$    | $N_a \times 256$ | agent positions from TrackFormer |
| $Q_M$    | $N_m \times 256$ | map features from MapFormer |
| $K$      | 6               | of forecasting modality in MotionFormer |
| $\hat{x}$ | $T \times 2$   | ground truth for motion forecasting |
| $\hat{x}$ | $N_a \times T \times 2$ | prediction of motion forecasting |
| $T$      | 12              | length of prediction timestamps in MotionFormer |
| $Q_{pos}$ | $N_a \times K \times 256$ | query position in MotionFormer |
| $Q_{ctx}$| $N_a \times K \times 256$ | query context in MotionFormer |
| $Q_a$    | $N_a \times K \times 256$ | motion query after agent-agent interaction in MotionFormer |
| $Q_m$    | $N_a \times K \times 256$ | motion query after agent-map interaction in MotionFormer |
| $Q_g$    | $N_a \times K \times 256$ | motion query after agent-goal point interaction in MotionFormer |
| $l$      | -               | index of decoder layer |
| $PE$     | -               | sinusoidal position encoding function |
| $I^s$    | $K \times T \times 2$ | scene-level anchor position in MotionFormer |
| $I^a$    | $K \times T \times 2$ | agent-level anchor position in MotionFormer |
| $\Phi$   | -               | kinematic cost function set |
| $T_o$    | 5               | length of prediction timestamps in OccFormer |
| $G^t$    | $N_a \times 256$ | agent feature input of $t^{th}$ block of OccFormer |
| $F^t$    | $200 \times 200 \times 256$ | future state output from $t^{th}$ block of OccFormer |
| $Q_X$    | $N_a \times 256$ | motion query (max-pooled on modality level) from the last layer of MotionFormer |
| $F^t_{ds}$ | $25 \times 25 \times 256$ | downscaled dense feature in $t^{th}$ block of OccFormer |
| $F^t_{dec}$ | $200 \times 200 \times 256$ | decoded dense feature after convolutional decoder of $t^{th}$ block of OccFormer |
| $D^t_{ds}$ | $25 \times 25 \times 256$ | agent-aware dense feature after pixel-agent interaction in $t^{th}$ block of OccFormer |
| $\hat{O}_A^t$ | $N_a \times 200 \times 200$ | instance-level probability map produced by $t^{th}$ block of OccFormer |
| $\hat{O}^t$  | $200 \times 200$ | classical instance-agnostic occupancy map merged from $\hat{O}_A^t$ for planning |
| $O^t_{att}$ | $200 \times 200$ | attention mask for pixel-agent interaction in $t^{th}$ block of OccFormer |
| $M^t$    | $N_a \times 256$ | mask feature of $t^{th}$ block of OccFormer |
| $U^t$    | $N_a \times 256$ | occupancy feature of $t^{th}$ block of OccFormer |
| $T_P$    | 6               | length of planning timestamps in Planner |
| $\hat{\tau}$ | $T_P \times 2$ | planned trajectory before the optimization with occupancy prediction |
| $\tau^*$ | $T_P \times 2$ | ultimate plan output |
| $\lambda$ | -               | Gaussian distribution |
| $\lambda$ | -               | hyperparameters in cost functions, target functions, etc. |

Table 12. **Lookup table of notations and hyperparameters.**
denoted as \( I_{s}^{a} \) is rotated and translated into the global coordinate frame according to each agent’s current location and heading angle, which is denoted as \( I_{T}^{a} \), as shown in Eq. (12),

\[
I_{i,T}^{s} = R_{a}I_{T}^{a} + T_{i},
\]

where \( i \) is the index of the agent, and it is omitted later for brevity. To facilitate the coarse-to-fine paradigm, we also adopt the goal point predicted from the previous layer \( \hat{x}_{T}^{-1} \). In the meantime, the agent’s current position is broadcast across the modality, denoted as \( \hat{x}_{0} \). Then, MLPs and sinusoidal positional embeddings are applied for each of the prior positional knowledge and we summarize them as the query context \( Q_{ctx} \), together build up our motion query. We set \( D = 256 \) throughout MotionFormer.

As shown in Fig. 4, our MotionFormer consists of three major transformer blocks, \textit{i.e.}, agent-agent, agent-map, and agent-goal interaction modules. The agent-agent interaction module is built upon standard transformer decoder layers, which are composed of a multi-head self-attention (MHSA) layer and a multi-head cross-attention (MHCA) layer, a feed-forward network (FFN) and several residual and normalization layers in between [8].

From the agent queries \( Q_{A} \) and map queries \( Q_{M} \), we also add the positional embeddings to those queries with sinusoidal positional embedding followed by MLP layers. The agent-goal interaction module is built upon deformable cross-attention module [96], where the goal point from the previous predicted trajectory \( (R_{a}\hat{x}_{T-1}^{a} + T_{a}) \) is adopted as the reference point, as shown in Fig. 5. Specifically, we set the number of sampled points to 4 per trajectory, and 6 trajectories per agent as we mention above. The output features of each interaction module are concatenated and projected with MLP layers to dimension \( D = 256 \). Then, we use Gaussian Mixture Model to build each agent’s trajectories, where \( \hat{x}_{i} \in \mathbb{R}^{K \times T \times 5} \). We set the prediction horizon \( T \) to 12 (6 seconds) in UniAD. Please note that we only take the first two of the last dimension (\textit{i.e.}, \( x \) and \( y \)) as final output trajectories. Besides, the scores of each modality are also predicted (\( \text{score} \ (\hat{x}_{i}) \in \mathbb{R}^{K} \)). We stack the overall modules for \( N \) times, and \( N \) is set to 3 in practice.

**E.4. Occupancy Prediction**

Given the BEV feature from upstream modules, we first downsample it by \( /4 \) with convolution layers for efficient multi-step prediction, then pass it to our proposed OccFormer. OccFormer is composed of \( T_{o} \) sequential blocks shown in Fig. 6, where \( T_{o} = 5 \) is the temporal horizon (including current and future frames) and each block is responsible for generating occupancy of one specific frame. Different from prior works which are short of agent-level knowledge, our proposed method incorporates both dense scene features and sparse agent features when unrolling the future representations. The dense scene feature is from the output of the last block (or the observed feature for current frame) and it’s further downsampled (\( /8 \)) by a convolution layer to reduce computation for pixel-agent interaction. The sparse agent feature is derived from the concatenation of track query \( Q_{A} \), agent positions \( P_{A} \), and motion query \( Q_{X} \), and it is then passed to a temporal-specific MLP for temporal sensitivity. We conduct pixel-level self-attention to model the long-term dependency required in some rapidly changing scenes, then perform scene-agent incorporation by attending each pixel of the scene to cor-
responding agents. To enhance the location alignment between agents and pixels, we restrict the cross-attention with an attention mask which is generated by a matrix multiplication between mask feature and downscaled scene feature, where the mask feature is produced by encoding agent feature with an MLP. We then upsample the attended dense feature to the same resolution as input $F_{t-1}^{\text{dec}}$ (4) and add it with $F_{t-1}^{\text{dec}}$ as a residual connection for stability. The resulting feature $F_t$ is both sent to the next block and a convolutional decoder for predicting occupancy at the original BEV resolution (/1). We reuse the mask feature and pass it to another MLP to form occupancy feature, and the instance-level occupancy is therefore generated by a matrix multiplication between occupancy feature and decoded dense feature $F_{t \text{dec}}$. Note that the MLP layer for mask feature, the MLP layer for occupancy feature, and the convolutional decoder are shared across all $T_o$ blocks while other components are independent in each block. Dimensions of all dense features and agent features are 256 in OccFormer.

Figure 6. **OccFormer.** It is composed of $T_o$ sequential blocks where $T_o$ is the temporal horizon (including current and future frames) and each block is responsible for generating occupancy of one specific frame. We incorporate both dense scene features and sparse agent features, which are encoded from upstream track query $Q_A$, agent position $P_A$ and motion query $Q_X$, to inject agent-level knowledge into future scene representations. We form instance-level occupancy $\hat{O}_A^t$ via a matrix multiplication between agent-level feature and decoded dense feature at the end of each block.

As shown in Fig. 7, our planner takes the ego-vehicle query generated from the tracking and motion forecasting module, which is symbolized with the blue triangle and yellow rectangle respectively. These two queries, along with the command embedding, are encoded with MLP layers followed by a max-pooling layer across the modality dimension, where the most salient modal features are selected and aggregated. The BEV feature interaction module is built with standard transformer decoder layers, and it is stacked for $N$ layers, where we set $N = 3$ here. Specifically, it cross-attends the dense BEV feature with the aggregated plan query. More qualitative results can be found in Appendix F.4 showing the effectiveness of this module. To embed location information, we fuse the plan-query with learned position embedding and the BEV feature with sinusoidal positional embedding. We then regress the planning trajectory with MLP layers, which is denoted as $\hat{\tau} \in \mathcal{R}^{T_p \times 2}$. Here we set $T_p = 6$ (3 seconds). Finally, we devise the collision optimizer for obstacle avoidance, which takes the predicted occupancy $\hat{O}$ and trajectory $\hat{\tau}$ as input as Eq. (10) in the main paper. We set $d = 5$, $\sigma = 1.0$, $\lambda_{\text{coord}} = 1.0$, $\lambda_{\text{obs}} = 5.0$.

Figure 7. **Planner.** $Q^{\text{ego}}_A$ and $Q^{\text{ego}}_{\text{ctx}}$ are the ego-vehicle query from the tracking and motion forecasting modules, respectively. Along with the high-level command, they are encoded with MLP layers followed by a max-pooling layer across the modality dimension, where the most salient modal features are selected and aggregated. The BEV feature interaction module is built with standard transformer decoder layers, and it is stacked for $N$ layers.

**E.5. Planning**
E.6. Training Details

Joint learning. UniAD is trained in two stages which we find more stable. In stage one, we pre-train perception tasks including tracking and online mapping to stabilize perception predictions. Specifically, we correspond pre-trained BEVFormer [48] weights to UniAD for fast convergence including image backbone, FPN, BEV encoder and detection decoder except for object query embeddings (due to the additional ego-vehicle query). We stop the gradient back-propagation in the image backbone to reduce memory cost and train UniAD for 6 epochs with tracking and online mapping losses as follows:

\[ L_1 = L_{\text{track}} + L_{\text{map}}. \]  

(13)

In stage two, we keep the image backbone frozen as well, and additionally freeze BEV encoder, which is used for view transformation from image view to BEV, to further reduce memory consumption with more downstream modules. UniAD now is trained with all task losses including tracking, mapping, motion forecasting, occupancy prediction, and planning for 20 epochs (for various ablation studies in main paper, it’s trained for 8 epochs for efficiency):

\[ L_2 = L_{\text{track}} + L_{\text{map}} + L_{\text{motion}} + L_{\text{occupancy}} + L_{\text{plan}}. \]  

(14)

Detailed losses and hyperparameters within each term of \( L_1 \) and \( L_2 \) are described below individually. The length of each training sequence (at each step) for tracking and BEV feature aggregation [48] in both stages is 5 (3 in ablation studies for efficiency).

Detection&tracking loss. Following BEVFormer [48], the Hungarian loss is adopted for each paired result, which is a linear combination of a Focal loss [53] for class labels and an \( l_1 \) for 3D boxes localization. In terms of the matching strategy, candidates from newborn queries are paired with ground truth objects through bipartite matching, and predictions from track queries inherit the assigned ground truth index from previous frames. Specifically, \( L_{\text{track}} = \lambda_{\text{focal}} L_{\text{focal}} + \lambda_{l_1} L_{l_1} \), where \( \lambda_{\text{focal}} = 2 \) and \( \lambda_{l_1} = 0.25 \).

Online mapping loss. As in [49], this includes thing losses for lanes, dividers, and contours, also a stuff loss for drivable area, where Focal loss is responsible for classification, \( L_1 \) loss is responsible for thing boxes, Dice loss and GIoU loss [70] account for segmentation. Detailedly, \( L_{\text{track}} = \lambda_{\text{focal}} L_{\text{focal}} + \lambda_{l_1} L_{l_1} + \lambda_{\text{giou}} L_{\text{giou}} + \lambda_{\text{dice}} L_{\text{dice}} \), with \( \lambda_{\text{focal}} = \lambda_{\text{giou}} = \lambda_{\text{dice}} = 2 \) and \( \lambda_{l_1} = 0.25 \).

Motion forecasting loss. Like most of the prior methods, we model the multimodal trajectories as gaussian mixtures, and use the multi-path loss [12, 79] which includes a classification score loss \( L_{\text{cls}} \) and a negative log-likelihood loss term \( L_{\text{reg}} \), and \( \lambda \) denotes the corresponding weight:

\[ L_{\text{motion}} = \lambda_{\text{cls}} L_{\text{cls}} + \lambda_{\text{reg}} L_{\text{reg}}, \]  

where \( \lambda_{\text{cls}} = \lambda_{\text{reg}} = 0.5 \). To ensure the temporal smoothness of trajectories, we predict agents’ speed at each timestep first and accumulate it across time to obtain their final trajectories.

Occupancy prediction loss. The output of instance-level occupancy prediction is a binary segmentation of each agent, therefore we employ binary cross-entropy and Dice loss [58] as the occupancy loss. Formally, \( L_{\text{occ}} = \lambda_{\text{bce}} L_{\text{bce}} + \lambda_{\text{dice}} L_{\text{dice}} \), with \( \lambda_{\text{bce}} = 5 \) and \( \lambda_{\text{dice}} = 1 \). Additionally, since the attention mask in the pixel-agent interaction module could be seen as a coarse prediction, we employ an auxiliary occupancy loss with the same form to supervise it.

Planning loss. Safety is the most crucial factor in planning. Therefore, apart from the naive imitation \( l_2 \) loss, we employ another collision loss which keeps the planned trajectory away from obstacles as follows:

\[ L_{\text{col}}(\hat{\tau}, \delta) = \sum_{i,t} \text{IOU}(\text{box}(\hat{\tau}_t, w + \delta, l + \delta), b_{i,t}), \]  

(15)

\[ L_{\text{plan}} = \lambda_{\text{imi}} |\hat{\tau}, \hat{\tau}|_2 + \lambda_{\text{col}} \sum_{(\omega, \delta)} \omega L_{\text{col}}(\hat{\tau}, \delta), \]  

(16)

where \( \lambda_{\text{imi}} = 1 \), \( \lambda_{\text{col}} = 2.5 \), \((\omega, \delta)\) is a weight-value pair considering additional safety distance, \( \text{box}(\hat{\tau}_t, w + \delta, l + \delta) \) represents the ego bounding box with an increased size at timestamp \( t \) to keep larger safe distance, and \( b_{i,t} \) indicates each agent forecasted in the scene. In practice, we set \((\omega, \delta)\) to \((1.0, 0.0), (0.4, 0.5), (0.1, 1.0)\).

F. Experiments

F.1. Protocols

We follow most of the basic training settings as in BEVFormer [48] for both two stages with a batch size of 1, a learning rate of 2×10^{-4}, learning rate multiplier of the backbone 0.1 and AdamW optimizer [56] with a weight decay of 1×10^{-2}. The default size of BEV size is 200×200, covering BEV ranges of [-51.2m, 51.2m] for both X and Y axis with the interval as 0.512m. More hyperparameters related to feature dimensions are shown in Table 12. Experiments are conducted with 16 NVIDIA Tesla A100 GPUs.

F.2. Metrics

Multi-object tracking. Following the standard evaluation protocols, we use AMOTA (Average Multi-object Tracking Accuracy), AMOTP (Average Multi-object Tracking Precision), Recall, and IDS (Identity Switches)
to evaluate the 3D tracking performance of UniAD on nuScenes dataset. AMOTA and AMOTP are computed by integrating MOTA (Multi-object Tracking Accuracy) and MOTP (Multi-object Tracking Precision) values over all recalls:

$$\text{AMOTA} = \frac{1}{n-1} \sum_{r \in \{\frac{1}{n}, \frac{2}{n}, \ldots, 1\}} \text{MOTA}_r,$$

$$\text{MOTA}_r = \max(0, 1 - \frac{\text{FP}_r + \text{FN}_r + \text{IDS}_r - (1 - r)\text{GT}}{\text{GT}}),$$

where FP$_r$, FN$_r$, and IDS$_r$ represent the number of false positives, false negatives and identity switches computed at the corresponding recall $r$, respectively. GT stands for number of ground truth objects in this frame. AMOTP can be defined as:

$$\text{AMOTP} = \frac{1}{n-1} \sum_{r \in \{\frac{1}{n}, \frac{2}{n}, \ldots, 1\}} \frac{\sum_{i,t} d_{i,t}}{\text{TP}_r},$$

where $d_{i,t}$ denotes the position error (in x and y axis) of matched track $i$ at time stamp $t$, and TP$_r$ is the number of true positives at the corresponding recall $r$.

**Online mapping.** We have four categories for the online mapping task, i.e., lanes, boundaries, pedestrian crossings and drivable area. We calculate the intersection-over-union (IoU) metric for each class between the network outputs and ground truth maps.

**Motion forecasting.** On one hand, following the standard motion prediction protocols, we adopt conventional metrics, including minADE (minimum Average Displacement Error), minFDE (minimum Final Displacement Error) and MR (Miss Rate). Similar to the prior works [50, 57, 65], these metrics are only calculated within matched TPs, and we set the matching threshold to 1.0m in all of our experiments. As for the MR, we set the MFE threshold to 2.0m. On the other hand, we also employ recently proposed end-to-end metrics, i.e., EPA (End-to-end Prediction Accuracy) [30] and minFDE-AP [65]. For EPA, we use the same setting as in ViP3D [30] for a fair comparison. For minFDE-AP, we do not separate ground truth into multiple bins (static, linear, and non-linearly moving sub-categories) for simplicity. Specifically, only when an object’s perception location and its min-FDE are within the distance threshold (1.0m and 2.0m respectively), it would be counted as a TP for the AP (average precision) calculation. Similarly to the prior works, we merge the car, truck, construction vehicle, bus, trailer, motorcycle, and bicycle as vehicle categories, and all the motion forecasting metrics provided in the experiments are evaluated on the vehicle category.

**Occupancy prediction.** We evaluate the quality of predicted occupancy in both whole-scene level and instance-level following [34, 92]. Specifically, the IoU measures the whole-scene categorical segmentations which is instance-agnostic, while the Video Panoptic Quality (VPQ) [43] takes into account each instance’s presence and consistency over time. The VPQ metric is calculated as follows:

$$\text{VPQ} = \sum_{t=0}^{H} \frac{\sum_{(p_t, q_t) \in \text{TP}_t \cap \cup(p_t, q_t)}}{|\text{TP}_t| + \frac{1}{2} |\text{FP}_t| + \frac{1}{2} |\text{FN}_t|} \times |t|,$$

where $H$ is the future horizon and we set $H = 4$ (which leads to $T_o = 5$ including the current timestamp) as in [34, 92], covering 2.0s consecutive data at 2Hz. TP$_t$, FP$_t$, and FN$_t$ are the set of true positives, false positives, and false negatives at timestamp $t$ respectively. Both two metrics are evaluated under two different BEV ranges, near for 30m x 30m and far for 100m x 100m around the ego vehicle. We evaluate the results of the current step ($t = 0$) and the future 4 steps together on both metrics.

**Planning.** We adopt the same metrics as in ST-P3 [37], i.e., L2 error and collision rate at various timestamps.

**F.3. Model scale**

We provide three variations of UniAD under different model scales as shown in Table 13. The chosen image backbones for image-view feature extraction are ResNet-50 [31], ResNet-101 and VoVNet 2-99 [45] for UniAD-S, UniAD-B and UniAD-L respectively. Since the model scale (image encoder) mainly influences the BEV feature quality, we could observe that the perceptual scores improve with a larger backbone, which further could lead to better prediction and planning performance.

**F.4. Qualitative results**

**Attention mask visualization.** To investigate the internal mechanism and show its explainability, we visualize the attention mask of the cross-attention module in the planner. As shown in Fig. 8, the predicted tracking bounding boxes, planned trajectory, and the ground truth HD Map are rendered for reference, and the attention mask is over-layered on top. From left to right, we show two consecutive frames in a time sequence but with different navigation commands. We can observe that the planned trajectory varies largely according to the command. Also, much attention is paid to the goal lane as well as the critical agents that are yielding to our ego vehicle.

**Visualization of different scenarios.** We provide visualizations for more scenarios, including cruising around the urban areas (Fig. 9), critical cases (Fig. 10), and obstacle avoidance scenarios (Fig. 11). Similarly, we show results
for all tasks in surround-view images, BEV, as well as the attention mask from the planner. A demo video\footnote{https://drive.google.com/file/d/1XkamTOHCUGetubblGCRMbv27t1ZdWsiW/view?usp=sharing} is also provided for reference.

**Failure cases** are essential for an autonomous driving algorithm to understand its weakness and guide the future work, and here we present some failure cases of UniAD. The failure cases of UniAD are summarized in two aspects mainly: (1) inaccurate results occur in prior modules while the later tasks could still recover, as shown in Fig. 12; (2) all modules are affected under some long-tail scenarios, as depicted in Fig. 13 and Fig. 14.

| Methods | Encoder | Tracking | Mapping | Motion Forecasting | Occupancy Prediction | Planning |
|---------|---------|----------|---------|-------------------|----------------------|----------|
|         | AMOTA↑  | AMOTP↑   | IDS↓    | IoU-lane↑         | IoU-road↑           | MR↓      |
| UniAD-S | R50     | 0.241    | 1.448   | 958               | 0.315 0.689         | 0.788 1.126 | 0.156 0.381 | 35.6 49.2 | 28.9 | 1.04 | 0.32 |
| UniAD-B | R101    | 0.359    | 1.320   | 906               | 0.313 0.691         | 0.708 1.025 | 0.151 0.456 | 63.4 40.2 | 54.7 | 33.5 | 1.03 | 0.31 |
| UniAD-L | V2-99+  | 0.409    | 1.259   | 1583              | 0.323 0.709         | 0.723 1.067 | 0.158 0.508 | 64.1 42.6 | 55.8 | 36.9 | 1.03 | 0.29 |

Table 13. **Comparisons between three variations of UniAD.** ∗: pre-trained with extra depth data [64].
Figure 8. **Effectiveness of navigation command and attention mask visualization.** Here we demonstrate how the attention is paid in accordance with the navigation command. We render the attention mask from the BEV interaction module in the planning module, the predicted tracking bounding boxes as well as the planned trajectory. The navigation command is printed on the bottom left, and the HD Map is rendered only for reference. From left to right, we show two consecutive frames in a time sequence but with different navigation commands. We can observe that the planned trajectory varies largely according to the command. Also, much attention is paid to the goal lane as well as the critical agents that are yielding to our ego-vehicle.

Figure 9. **Visualization for cruising around the urban areas.** UniAD can generate high-quality interpretable perceptual and prediction results, and make a safe maneuver. The first three columns show six camera views, and the last two columns are the predicted results and the attention mask from the planning module respectively. Each agent is illustrated with a unique color. Only top-1 and top-3 trajectories from motion forecasting are selected for visualization on images-view and BEV respectively.
Figure 10. **Critical case visualizations.** Here we demonstrate two critical cases. The first scenario (top) shows that the ego vehicle is yielding to two pedestrians crossing the street, and the second scenario (down) shows that the ego vehicle is yielding to a fast-moving car and waiting to go straight without protection near an intersection. We can observe that much attention is paid to the most critical agents, *i.e.*, pedestrians and fast-moving vehicles, as well as the intended goal location.

Figure 11. **Obstacles avoidance visualization.** In these two scenarios, the ego vehicle is changing lanes attentively to avoid the obstacle vehicle. From the attention mask, we can observe that our method focuses on the obstacles as well as the road in the front and back.
Figure 12. **Failure cases 1.** We show a failure case where inaccurate results occur in prior modules while the later tasks could still recover. The top row and the down row represent two consecutive frames from the same scenario. The vehicle in the red circle is moving from a far distance toward the intersection at a high speed. It is observed that the tracking module misses it at first, then captures it at the latter frame. The blue circles show a stationary car yielding to the traffic, and it is missed in both frames. Interestingly, both vehicles show strong reactions to the attention masks of the planner, even though they are missed in the prior modules. It means that our planner still pays attention to those critical though missed agents, which is intractable in previous fragmented and non-unified driving systems, and demonstrates the robustness of UniAD.

Figure 13. **Failure cases 2.** Here we present a long-tail scenario, where a large trailer with a white container occupies the entire road. We can observe that our tracking module fails to detect the accurate size of the front trailer and heading angles of vehicles beside the road.

Figure 14. **Failure cases 3.** In this case, the planner is over-cautious about the incoming vehicle in the narrow street. The dark environment is one critical type of long-tail scenarios in autonomous driving. Applying smaller collision loss weight and more regulation regarding the boundary might mitigate the problem.