STSBench: A Spatio-temporal Scenario Benchmark for Multi-modal Large Language Models in Autonomous Driving

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Code: `https://github.com/LRP-IVC/STSBench`
Data: `https://huggingface.co/datasets/ivc-lrp/STSBench`

Abstract

We introduce STSBench, a scenario-based framework to benchmark the holistic understanding of vision-language models (VLMs) for autonomous driving. The framework automatically mines predefined traffic scenarios from any dataset using ground-truth annotations, provides an intuitive user interface for efficient human verification, and generates multiple-choice questions for model evaluation. Applied to the nuScenes dataset, we present STSnu, the first benchmark that evaluates the spatio-temporal reasoning capabilities of VLMs based on comprehensive 3D perception. Existing benchmarks typically target off-the-shelf or fine-tuned VLMs for images or videos from a single viewpoint, focusing on semantic tasks such as object recognition, dense captioning, risk assessment, or scene understanding. In contrast, STSnu evaluates driving expert VLMs for end-to-end driving, operating on videos from multi-view cameras or LiDAR. It specifically assesses their ability to reason about both ego-vehicle actions and complex interactions among traffic participants, a crucial capability for autonomous vehicles. The benchmark features 43 diverse scenarios spanning multiple views and frames, resulting in 971 human-verified multiple-choice questions. A thorough evaluation uncovers critical shortcomings in existing models' ability to reason about fundamental traffic dynamics in complex environments. These findings highlight the urgent need for architectural advancements that explicitly model spatio-temporal reasoning. By addressing a core gap in spatio-temporal evaluation, STSBench enables the development of more robust and explainable VLMs for autonomous driving.

1 Introduction

The rapid development of increasingly powerful vision-language models (VLMs) [4, 7, 8, 10, 31, 32, 37–39] has sparked significant interest in applying them to end-to-end autonomous driving [17, 23, 28, 33, 46, 49, 51, 57, 65, 67, 68]. These models aim to enhance trust in fully autonomous systems by providing human-interpretable decisions in natural language [60]. Unlike pretrained generalist

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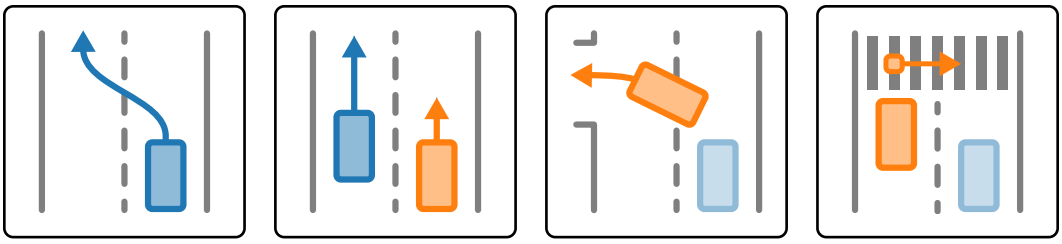

(a) Ego. (b) Agent-to-Ego. (c) Agent. (d) Agent-to-Agent.

Figure 1: **STSBench scenario categories.** The benchmark covers common ego-vehicle (blue) actions, *e.g.*, *ego lane change* (a) and interactions with agents (orange), *e.g.*, *ego overtaking agent* (b), important for vehicle control. In addition, to test for complex spatio-temporal understanding, we evaluate agent actions, *e.g.*, *agent left turn* (c), and interactions between agents, *e.g.*, *agent waiting for pedestrian to cross* (d).

VLMs, these driving experts operate on consecutive multi-view images or LiDAR scans to understand a scene comprehensively and are fine-tuned for planning and controlling the ego vehicle.

To achieve end-to-end driving, where raw sensor inputs are directly mapped to driving actions, most models [28, 57, 68] predict future trajectories through waypoints or control signals for the ego vehicle. A common evaluation strategy is to perform open-loop planning on nuScenes [6], as most other real-world planning datasets lack raw visual inputs alongside map data and agent trajectories, or are synthetic benchmarks [26] simulated in CARLA [16]. A drawback of the open-loop evaluation on nuScenes [6], however, is the relatively small and unbalanced validation split [36] in which, for approximately 75% of all cases, the correct action is "continue to drive straight". Moreover, evaluating the L2 error between predicted and ground truth waypoints, or measuring the accuracy of ego-action predictions, offers limited insight into the decision-making and reasoning capabilities of language-based end-to-end driving experts. Therefore, further testing of these models is crucial.

A growing number of benchmarks assess the understanding of VLMs in the context of automated driving [19, 34, 41, 43, 48, 50, 53, 60, 64]. They typically focus on specific abilities such as spatial reasoning in camera images [19, 53], recognition and prediction of ego-vehicle actions [43, 50], the handling of visual corruptions [60], or understanding risk [41, 48] and critical driving scenarios [64]. However, most of these benchmarks target general-purpose VLMs that operate on single images or monocular videos and are not designed to evaluate whether models can jointly reason over spatially distributed and temporally extended inputs from multi-view video or LiDAR data, which is an essential capability for coherent understanding in complex, real-world driving scenes. Furthermore, most existing action- or event-based benchmarks evaluate only the behavior of the ego vehicle. While this focus is reasonable for planning and control tasks, it overlooks the broader situational understanding required for safe driving, such as anticipating interactions between other traffic participants (agents). Even if they are not of immediate importance, driving models should have the ability to understand such actions or the future consequences of events.

Another major challenge lies in developing annotation schemes for benchmarks applicable to existing perception or planning datasets without requiring extensive manual effort. Existing driving-related benchmarks [29, 30, 43, 48, 50, 54, 60] are typically tied to a specific dataset through manual annotations or extensive human verification. However, although many driving datasets [6, 42, 52, 58] are recorded using multi-camera and LiDAR systems, their sensor setups differ significantly regarding camera type, placement, and orientation. As a result, a model with 3D understanding [35, 56] trained and evaluated on one dataset cannot be straightforwardly assessed using a benchmark built for another, since the projection from images to 3D space depends on the dataset-specific calibration. This makes it necessary to create separate benchmark annotations for each dataset, which is both time-consuming and costly when done manually.

To address the identified issues, we introduce STSBench, a generalizable framework for automatically mining spatio-temporal driving scenarios from existing datasets with rich ground-truth annotations. The framework identifies agent-centric traffic scenarios, following a predefined scenario catalog, that reflect real-world interactions by leveraging information such as 3D bounding boxes and tracks, agent class labels, ego-motion data, and HD maps. The catalog contains all scenarios and their

Table 1: **Task-specific driving benchmarks.** Autonomous driving benchmarks created from the nuScenes [6] dataset focusing on various tasks grouped by dataset source. †: we do not consider simple status classification annotations such as *moving*, *walking*, *etc*. as temporal reasoning. Annotation modalities denote single images (S.I.), multi-view images (M.I.), and multi-view videos (M.V.). Evaluation types are: Visual Question Answering (VQA), Multiple Choice (MC), Numerical (NUM), and Open-loop Planning (OLP).

Benchmark Name	Anno. Modality	Anno. Type	Human Verif.	Spat. Reas.	Temp. Reas.†	Multi-view Events	Third Party Interaction	Eval. Type	Pub. Avail.
DriveMLLM [19]	S.I.	Auto	✓	✓	✗	✗	✗	MC, NUM	✓
NuScenes-MQA [24]	M.I.	Auto	✗	✓	✗	✗	✗	VQA	✓
NuScenes-QA [47]	M.I.	Auto	✗	✓	✗	✗	✗	VQA	✓
DriveLM [50]	M.I.	Manual	✓	✓	✗	✓	✓	VQA	✓
NuScenes-SpatialQA [53]	M.I.	Auto	✗	✓	✗	✗	✗	MC, NUM	✗
DriveBench [60]	M.I.	Manual	✗	✓	✗	✓	✓	VQA	✓
NuInstruct [15]	M.V.	Auto	✗	✓	✓	✓	✗	VQA	✓
TOD3Cap [29]	M.V.	Manual	✓	✓	✗	✗	✗	VQA	✓
DriveLLM-o1 [25]	M.I.	Auto	✓	✓	✓	✗	✗	VQA, MC	✓
OmniDrive [57]	M.V.	Auto	✓	✓	✓	✗	✗	VQA, OLP	✓
STSBench3D (ours)	M.V.	Auto	✓	✓	✓	✓	✓	MC	✓

definitions. Each scenario is also assigned a list of negative scenarios that most of the time should not occur concurrently (e.g., *left turn* and *overtaking*), representing negative answer candidates for the subsequent question generation. In addition to this fully automated extraction procedure, we provide a visual inspection tool that enables fast and effortless human verification of the mined scenarios. Inspectors are tasked to check for false positive scenarios (*i.e.*, mined but do not apply) and remove predefined negative ones that also occur during the corresponding scenario (*e.g.*, for a vehicle increasing its speed while performing a *right turn*, the negative scenario *accelerate* would be removed when *right turn* is the mined positive scenario). From the verified scenarios, STSBench automatically constructs a multiple-choice benchmark that asks models to identify which interactions occur in a given scene. In particular, the benchmark tests for the correct identification and understanding of agent-related spatio-temporal scenarios. Questions may concern the behavior of the ego vehicle, the actions of other agents (such as vehicles, pedestrians, or cyclists), interactions between the ego vehicle and other agents, or among multiple third-party agents. Examples of the different categories are illustrated in Fig. 1. The workflow is simple: automatically mine scenarios, verify them with minimal effort, and convert them into a structured spatio-temporal reasoning task.

Furthermore, we instantiate STSBench on the validation split of the nuScenes dataset, which remains the most commonly used training and evaluation dataset for vision-language models in autonomous driving. Unlike existing benchmarks that focus narrowly on ego-centric actions in images or monocular videos, our benchmark, STSnu, explicitly targets spatio-temporal reasoning involving both ego and non-ego agents across multiple views and time steps (see Table 1). STSnu comprises 43 scenarios resulting in a total of 971 challenging multiple-choice questions.

We conduct a detailed evaluation of various models that fall into one of three categories: text-only large language models (LLMs), off-the-shelf VLMs, or driving expert VLMs. While LLMs receive ground truth trajectories in text form, off-the-shelf VLMs operate on multiple images. Expert models are designed to deal with consecutive multi-view images (videos). With just trajectory information available, LLMs outperform both VLM counterparts significantly. Our evaluations highlight that state-of-the-art models across all categories provide limited spatio-temporal reasoning capabilities. This is especially notable for more challenging scenarios (involving interactions between other agents), which require a truly holistic understanding of the scene.

2 Related Work

Driving datasets and benchmarks with text annotations. Autonomous driving (AD) is an extensive field of research that has led to the creation of numerous datasets [6, 9, 18, 42, 52, 58, 63] for various perception tasks. These datasets have been enriched with text annotations to facilitate language-based model training for specific tasks in the AD domain. Following common practices in visual instruction tuning [10, 37, 32], annotations have been added mostly for separate multi-view

images, focusing on tasks such as grounding [13, 55], ego-action prediction [30, 61], open-loop planning [50, 54], risk assessment [14, 41], spatial reasoning [19, 53], or visual question answering [43, 44, 34]. To address the lack of 3D understanding, EML [69] introduces text annotations that incorporate question-answer pairs about 2D-to-3D spatio-temporal relations. The first attempts to evaluate the spatial capabilities of vision-language models for AD are the benchmarks DriveM-LLM [19], NuScenes-MQA [24], and NuScenes-SpatialQA [53]. They asses VLMs for their ability to measure distances and understand relative positions within camera images. However, since autonomous driving necessitates a holistic understanding of dynamic scenes, various datasets that incorporate multi-view video [15, 57] or 3D [47, 29, 59, 48] annotations emerged. Datasets such as Nuscenes-QA [47], DriveLM [50], OmniDrive [57], and NuInstruct [15] propose visual question-answering frameworks aimed at scene understanding, chain-of-thought reasoning and counterfactual reasoning. Despite their extensive annotations, these datasets rely predominantly on question–answer pairs that emphasize semantics [47, 50] and spatial relations [15], with limited temporal context, particularly beyond ego-vehicle interactions. STSnu specifically targets these gaps and tests the spatio-temporal reasoning capabilities of end-to-end driving models.

Vision-language models for end-to-end driving. Vision-Language Models (VLMs) [4, 8, 12, 2, 32, 38, 10] have attracted a lot of attention due to their exceptional zero-shot capabilities. These capabilities have also raised interest in applying these models to end-to-end AD for open-loop and closed-loop planning. Early methods directly apply VLMs to the front-view camera images of an autonomous vehicle [3, 40, 50, 62, 66, 69] to predict future trajectories or control signals in text form. However, a holistic understanding of the traffic scene is crucial for realistic driving scenes with highly dynamic scenarios. Therefore, another line of work operates on multi-view images and videos [28, 22, 33, 57]. To cope with the increasing number of image tokens caused by additional views and multiple video frames, Senna [28] compresses each view via temporal attention for path planning. Another technique for dealing with multiple views is encoding into Bird's Eye View (BEV) features that are later aligned with the underlying LLM. While GPVL [33] and BEV-InMM [15] utilize a BEVFormer [35] backbone, OmniDrive [57] uses StreamPETR [56]. More recent approaches combine end-to-end driving models [20, 27] with VLMs [17, 46, 51, 68] to increase the contextual understanding and provide reasoning alongside future trajectories. Despite their excellent performance on the planning task, the variety of methods and their handling of available input modalities raise questions about their environmental understanding (*i.e.*, reasoning capabilities). Therefore, we conduct a detailed analysis of the spatio-temporal reasoning capabilities of language-based end-to-end driving models by applying STSBench to instantiate STSnu on nuScenes [6].

3 Spatio-temporal Scenario Benchmark

With STSBench, we introduce a benchmark framework designed to evaluate the spatio-temporal reasoning capabilities of vision-language models (VLMs) in autonomous driving. While most existing benchmarks focus on off-the-shelf or fine-tuned VLMs operating on single images or monocular videos, our benchmark targets expert driving models. These experts are expected to have a comprehensive 3D understanding of dynamic scenes and, therefore, need to process multi-view, LiDAR, or a combined video input signal that enables holistic reasoning. The development of our benchmark is motivated by two observations:

There is a gap in assessing the spatio-temporal understanding of expert driving models. Recent efforts have adapted VLMs for driving [23, 28, 57] or extended existing planning models such as UniAD [20] with LLMs [68] to improve interpretability and trust. However, these expert models are usually evaluated on the nuScenes [6] dataset using predicted waypoints or control signals, with metrics such as L2 error or collision rate. Even if these scores are excellent, they do not guarantee that the model's decisions are grounded in a correct understanding of other traffic participants or scene dynamics. Although several benchmarks have been developed to test off-the-shelf VLMs for spatial [19, 24, 53] or temporal [15, 25] reasoning, most are restricted to single frames or monocular views. NuInstruct [15] remains an exception by providing multi-view video-based questions, but it is automatically generated and lacks human verification, making it better suited for training than evaluation. Additionally, the temporal reasoning aspect of the NuInstruct benchmark is limited to rather simple motion states, such as whether an agent is moving or stopped.

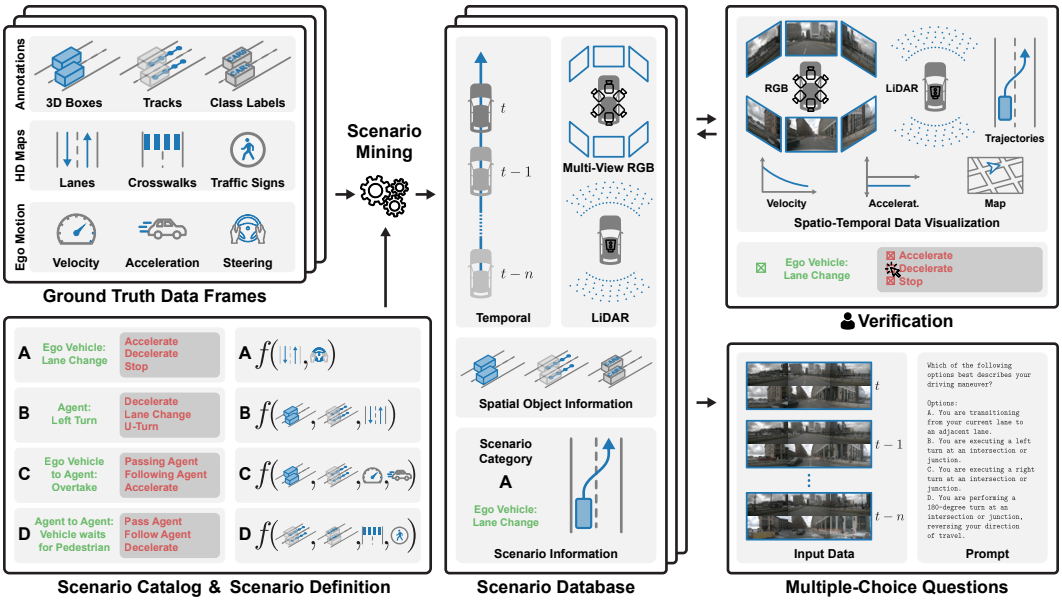

Figure 2: **STSBench workflow.** (Best viewed on screen)

Existing benchmarks are tailored for a specific dataset and can hardly be transferred or extended by additional scenarios. Encoding a 3D scene from multiple 2D images implicitly requires knowledge of the transformations that relate each image to a shared 3D space. Most recent detection encoders [35, 56], commonly used in end-to-end driving models, learn this mapping during training. As a result, they become tied to a fixed sensor setup for which they can reason accurately about object sizes and distances. This reliance on specific camera setups makes it difficult to evaluate a model trained on one dataset using the benchmark of another, unless domain adaptation or generalization strategies are employed. Therefore, it is essential to have a fast and generalizable framework applicable to various datasets with different sensor configurations. Moreover, existing benchmarks are often built by manually annotating data [29, 50], making them time-consuming and expensive to replicate. Even when using the same dataset, adding a new benchmark task typically requires inspecting and re-annotating a large number of samples. These challenges underscore the need for a fast and generalizable framework for benchmark creation.

To address these challenges, we introduce STSBench, a framework for fast and scalable traffic scenario mining and verification. In Section 3.1, we describe the annotation pipeline that transforms ground truth perception and map annotations of any dataset into structured multiple-choice evaluations for spatio-temporal reasoning. Section 3.2 details the instantiation of this framework on the nuScenes [6] dataset, resulting in our STSnu benchmark.

3.1 Annotation Framework

Our dataset-agnostic annotation framework aims to create an accurate benchmark for any given perception dataset (*e.g.*, [6, 42, 52]), considering all available ground truth annotations for the respective dataset. These annotations include 3D bounding boxes, tracking identifiers, agent class labels, ego-motion data (*e.g.*, velocity, acceleration, steering angle), or HD map data (*e.g.*, lanes, lane boundaries, crosswalks). In Fig. 2, we illustrate the benchmark creation workflow of STSBench.

1) Scenario catalog. To build a coherent benchmark, we define a scenario catalog containing all relevant scenarios (*e.g.*, lane change, overtake, following, *etc.*). Additionally, we predefine a list of negative scenarios for each entry in the catalog. Negative scenarios are other scenarios that should not occur for the same agent concurrently and serve as wrong answer candidates in our question generation. Assume we have an *overtaking* scenario in which an agent (vehicle) in motion passes another agent (vehicle), also in motion, in the adjacent lane. Closely related scenarios would be *passing*, where only one of the two vehicles is moving, and *acceleration*, where a vehicle increases its speed. For an actual *overtaking* scenario, both *passing* and *acceleration* are valuable negatives

(assuming they have no semantic or temporal overlap) to test the reasoning capabilities: Holistic spatio-temporal understanding implies that also closely related scenarios can be distinguished.

2) Scenario definition. To enable automated mining of predefined traffic scenarios, we specify heuristics using only ground-truth annotations from the target dataset. For instance, an important scenario crucial for driving experts is recognizing *lane changes* for the ego vehicle and other vehicles in the scene. The complexity of this action requires knowing the position of the corresponding vehicle throughout multiple frames w.r.t. lane boundaries. The event gets recognized as such if the boundary is crossed and a vehicle transitions from one lane to another.

3) Scenario mining. We automatically mine the predefined scenarios and save them in a scenario database. The database contains references to visual data, such as consecutive images of all available views and LiDAR data, the spatial coordinates of all objects involved in the scenario, and the extracted scenario information, including the found scenario and assigned negatives.

4) Verification. Human verification is used to ensure the quality of annotations. Rather than reviewing full sequences frame by frame, the annotator only needs to perform two simple checks: confirm or reject the presence of a mined agent scenario and verify that all assigned negative scenarios do not apply to the same agent. For instance, in a mined *lane change* scenario, the same agent might also reduce its speed (*deceleration*), which would consequently represent an invalid negative scenario if predefined in the scenario catalog (see Fig. 2, verification). In this example, the annotator would remove *deceleration* from the list of negative scenarios. These checks are lightweight and fast, allowing for efficient quality control without the burden of traditional manual annotation.

5) Question generation. Finally, STSBench generates multiple-choice questions asking which of the provided scenario examples occur in the scene. For different scenario types, *i.e.*, ego, agent, ego-to-agent, and agent-to-agent, we provide fixed questions containing the required spatial positions of the relevant agents. The questions are designed to have one correct answer and, by default, provide five possible choices. Further details are provided in the supplementary material.

3.2 STSnu Benchmark Construction

We leverage STSBench to mine scenarios and subsequently derive multiple-choice questions from a real-world dataset for evaluating the spatio-temporal reasoning capabilities of end-to-end driving models.

Data Source. Since most expert driving models [21, 29, 54, 57] operate on the multi-view videos or LiDAR scans of nuScenes [6], we construct our benchmark on this large-scale autonomous driving dataset with rich 3D annotations in a multi-sensor setup. In particular, we automatically gather scenarios from all 150 scenes of the validation set, considering only annotated key frames. Therefore, we leverage manually annotated 3D tracks and agent class labels, ego-motion data (*e.g.*, velocity) from the inertial measurement unit (IMU), and lanes, lane boundaries, and road markings (*e.g.*, crosswalks) from the available HD map data.

In contrast to prior benchmarks, focusing primarily on ego-vehicle actions that mainly occur in the front view, STSnu evaluates spatio-temporal reasoning across a broader set of interactions and multiple views. This includes reasoning about other agents and their interactions with the ego vehicle or with one another. To support this, we define four distinct scenario categories:

1) Ego-vehicle scenarios. The first category includes all actions related exclusively to the ego vehicle, such as *acceleration/deceleration*, *left/right turn*, or *lane change*. For control decisions and collision prevention, driving models must be aware of the ego vehicle's state and behavior. Although these scenarios are part of existing benchmarks in different forms and relatively straightforward to detect, they provide valuable negatives for scenarios with ego-agent interactions.

2) Agent scenarios. Similar to ego-vehicle scenarios, agent scenarios involve a single agent in the scene. However, this category also includes vulnerable road users, such as pedestrians and cyclists. Pedestrians, contrary to vehicles, perform actions such as *walking*, *running*, or *crossing*. Awareness of other traffic participants and their actions is crucial when assessing risk, planning the next course

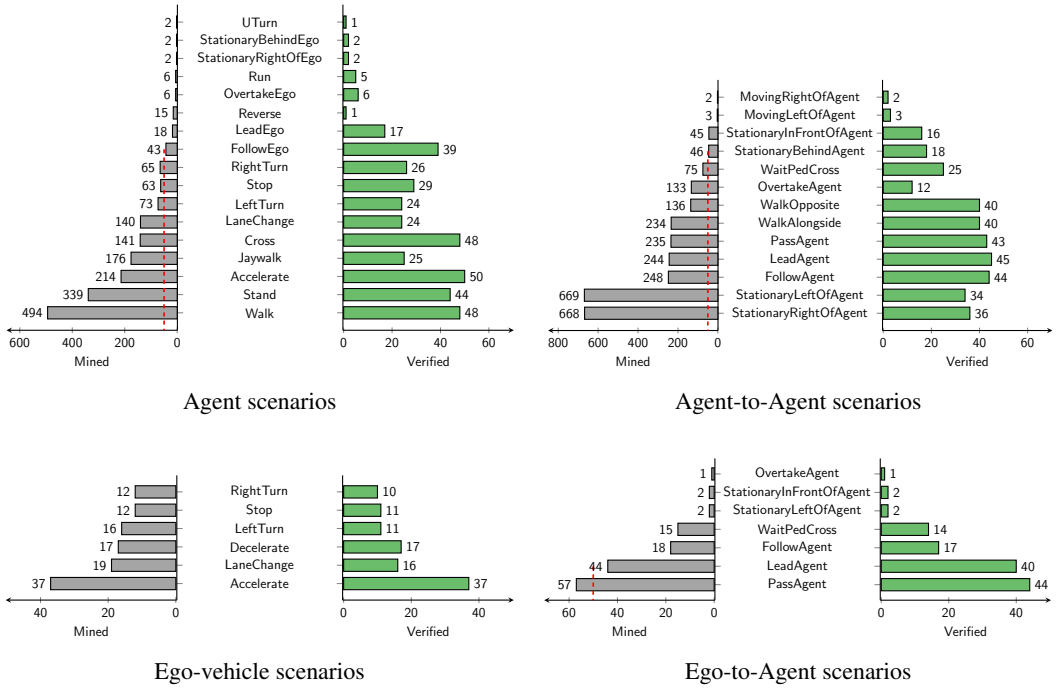

Figure 3: **Scenario statistics.** Number of mined scenarios in total (gray) and the remaining samples (green) after sub-sampling and verification. Scenarios with more than 50 samples (dashed red line) have been sub-sampled considering spatial distribution, occlusion, and distance to the ego-vehicle.

of action, or analyzing the situation in a dynamic environment. In contrast to ego-vehicle actions, other road users may be occluded or far away, posing a particular challenge.

3) Ego-to-agent scenarios. The third category of scenarios describes ego-related agent actions. Directly influencing the driving behavior of each other, this category is similarly important to the ego-vehicle scenarios w.r.t. the immediate control decisions. Ego-agent scenarios contain maneuvers such as *overtaking*, *passing*, *following*, or *leading*. The scenarios focus on agents in the immediate vicinity of the ego vehicle and direct interactions.

4) Agent-to-agent scenarios. The most challenging group of scenarios concerns interactions between two agents, not considering the ego vehicle. These scenarios describe the spatio-temporal relationship between objects. For instance, a vehicle that *overtakes* another vehicle in motion or pedestrians *moving alongside* each other. The latter is a perfect example of interactions that do not actively influence the driving behavior of the expert model. However, we argue that a holistic understanding of the scene should not be restricted to the immediate surroundings of the ego vehicle.

3.3 Benchmark Statistics

The scenario catalog of our STSnu benchmark comprises 43 different scenario descriptions. Using this catalog, STSBench has automatically mined 4790 scenarios from 150 sequences of the nuScenes [6] validation set. To ensure a better balance of the benchmark, we sub-sampled overrepresented scenarios based on occlusion rate and the spatial distribution of agents. Hence, with this optional step, we removed very difficult examples of highly occluded agents and objects that are far away. The remaining 1188 scenarios have gone through human verification and finally resulted in 971 multiple-choice

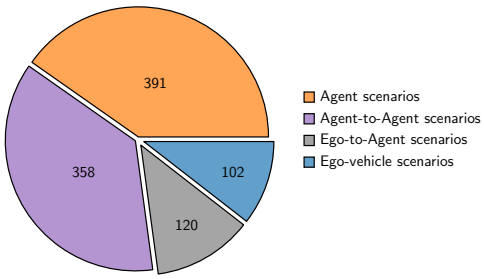

Figure 4: **Scenario distribution.** Number of scenarios per category.

questions offering at least five possible answers per question, of which exactly one is correct. We provide detailed numbers of mined, sub-sampled, and remaining scenarios after human verification in Fig. 3. The distribution of scenarios assigned to the four proposed categories is illustrated in Fig 4. We can see that a large proportion of the scenarios cover the two more difficult scenario categories, *i.e.*, agent and agent-to-agent. Despite this, the ego and ego-to-agent scenarios, some of which were also examined in other benchmarks, are sufficiently represented. We provide additional statistics and details of STSnu in the supplementary material.

Verification and correction. To ensure accuracy, the verification was conducted by three different individuals with a European Class B driver's license. Prior to the validation procedure, the human driving experts were briefed to gain a general understanding of the scenarios and what requirements they needed to meet. The agreement on correctly mined scenarios was 85.6% (1017 agreements out of 1188) while there was a disagreement of 20.8% (247 out of 1188) on assigned negative scenarios, which results in a Fleiss' kappa of 0.87 and 0.97, respectively. This confirms consistent verifications across all experts. There were mainly differences in the perception of recognizable and unrecognizable agents, as well as misunderstandings of interactions between two agents. On average, the three inspectors spent 4.78 hours each verifying the data, which is around 14.5 seconds per sample and inspector. A more detailed analysis and verification times are provided in the supplementary material. For the final STSnu benchmark, we merged verified scenarios applying a majority voting and kept all assigned negative scenarios with full agreement over all reviewers. This conservative approach is designed to minimize ambiguity in answer choices and ensure high annotation quality.

4 Experiments

The evaluation on STSnu follows a simple protocol. For each scenario, we measure accuracy as the proportion of multiple-choice questions answered correctly. To account for scenario imbalance, we report the overall accuracy as a weighted mean across all scenarios. Beyond its simplicity, this evaluation method offers the significant advantage of being both interpretable and comparable across models.

Baselines. We evaluate a range of models from three categories: large-language models (LLMs), off-the-shelf vision-language models (VLMs), and driving expert VLMs. First, we task LLMs to infer the correct maneuver given ground-truth perception data (*i.e.*, ego-vehicle and agent trajectories). Therefore, we selected two open-source models, DeepSeek V3 [11] and Llama 3.2 [1], and one closed-source model, GPT-4o [45]. Second, for the evaluation of VLMs without fine-tuning, we use Qwen2.5-VL 7B [5], InternVL 2.5 1B [8], and InternVL 2.5 8B [8]. Third, as representative driving expert models, we evaluate Senna-VLM [28], OmniDrive [57], and DriveMM [21].

Evaluation setting. Since only driving expert models are designed to handle multi-view video data, we adapted the input format for LLMs and off-the-shelf VLMs in our evaluation. To simulate a perfect perception system, we provide LLMs with the GPS positions of the ego vehicle and, when relevant, the trajectories of involved agents, along with the task description, a multiple-choice question, and scenario definitions for the available answers. This setup serves as a simple baseline for comparison. For off-the-shelf VLMs, we supply a series of images and an adapted text prompt. Because scenarios can span multiple viewpoints, we select, at each time step, the image corresponding to the camera view in which the relevant part of the scenario occurs. The associated camera view metadata is also provided. Driving expert models, on the other hand, receive full multi-view image sequences in addition to the text prompt, in which we refer to the involved agents. Further implementation details and input formatting for all models are provided in the supplementary material.

Overall performance and analysis. The evaluation results in Table 2 indicate that VLMs, particularly driving expert VLMs, do not have a spatio-temporal understanding of dynamic traffic scenes. Driving expert VLMs are good at basic perception tasks, *i.e.*, observing traffic participants near the ego vehicle (ego-to-agent), but struggle with ego-vehicle and agent-to-agent scenarios, thus demonstrating insufficient holistic spatio-temporal understanding. In comparison, without image inputs, the top-performing LLM outperforms its visual counterparts by a significant margin, especially for relatively simple ego-vehicle (58.93% vs. 47.79%) and ego-to-agent (75.15% vs. 61.83%) scenarios. GPT-4o [45], the advanced reasoning model, performs particularly well, reaching an average accuracy

Table 2: **Overall performance.** Performance comparison of LLMs (text-only), off-the-shelf VLMs (multi-frame camera images), and driving expert VLMs (multi-view videos). The evaluation is run five times using different randomly selected negative scenarios (*i.e.*, wrong answer choices). Accuracies are grouped by scenario categories. The best results are highlighted in bold.

	Ego	Ego-to-Agent	Agent	Agent-to-Agent	Average
Llama 3.2 [1]	24.77 ±1.7	20.28 ± 5.0	17.31 ±1.7	25.93 ±2.9	22.07 ±1.8
DeepSeek V3 [11]	48.39 ±9.8	59.07 ± 8.2	43.19 ±2.3	**45.18** ±2.7	48.96 ±1.9
GPT-4o [45]	**58.93** ±3.1	**75.15** ± 2.8	**44.03** ± 2.2	42.97 ±3.4	**55.27** ±2.0
InternVL 2.5 1B [8]	19.93 ±4.3	**46.68** ± 8.9	23.86 ±6.5	24.76 ±3.9	28.81 ±3.4
Qwen2.5-VL 7B [5]	37.37 ±3.6	42.36 ± 7.5	35.87 ±4.0	37.84 ±1.6	38.36 ±1.8
InternVL 2.5 8B [8]	**38.43** ±2.4	44.58 ± 8.9	**47.19 ±1.2**	**43.81 ±4.7**	**43.50** ±3.6
Senna-VLM [28]	8.81 ±1.9	44.44 ± 7.2	26.10 ±5.0	**31.45** ±3.1	27.70 ±2.7
OmniDrive [57]	24.40 ±5.6	42.97 ± 8.8	23.78 ±1.7	26.15 ±3.8	29.33 ±2.2
DriveMM [21]	**47.79** ±5.0	**61.83** ±11.2	**38.70** ±2.3	27.95 ±4.6	**44.07** ±2.8

of 55.27%. DriveMM [21] performs with 44.07%, on average, second best to GPT-4o [45]. It leads among all visual models, but only by a narrow margin ahead of the off-the-shelf InternVL 2.5 8B [8].

An interesting observation is the considerable gap between DriveMM [21] and the other expert models, particularly for the ego scenarios. While OmniDrive [57] projects multi-view image features into BEV, DriveMM directly processes multi-view videos. It is worth noting that the StreamPETR [56] encoder of OmniDrive [57] was initially designed for perception tasks, such as 3D object detection, where it is crucial to model the surroundings of the ego vehicle. The results suggest that these representations may hamper the reasoning performance w.r.t. ego actions. We provide a more detailed analysis and qualitative results of all models in the supplementary material.

Number of multiple-choice options. To accommodate varying difficulty levels, our benchmark allows scaling the number of multiple-choice options. As shown in Fig. 5, increasing the number of options leads to a decrease in the accuracy of the DriveMM [21] model. This performance drop suggests that model predictions may also depend on the process of eliminating incorrect choices rather than a true understanding of the underlying scenario. Additionally, the increase in options results in greater variability in model performance, indicating increased task difficulty. We find that using five multiple-choice options offers an effective trade-off, which avoids both triviality and excessive complexity in the benchmark.

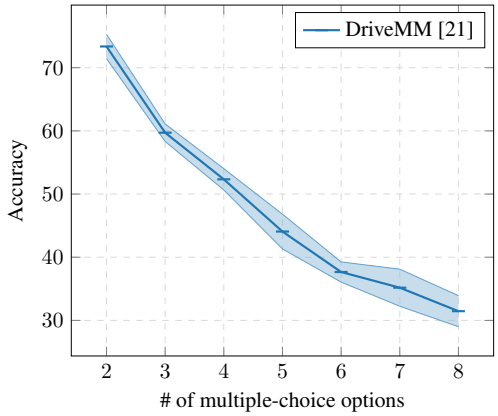

Figure 5: **Model performance over number of multiple-choice options.** Mean and variance of the DriveMM [21] accuracy across five independent evaluation runs, shown for increasing numbers of multiple-choice options (*e.g.*, two: A-B; three: A-B-C). In each evaluation, the order of the multiple-choice options was randomly permuted.

5 Conclusion

In this paper, we introduced STSBench, a framework for automatic scenario mining from large-scale autonomous driving datasets with rich ground-truth annotations. The framework also includes a fast and lightweight verification interface, enabling the effortless creation of high-quality benchmarks for spatio-temporal reasoning in multi-view video or LiDAR data. We applied STSBench to the nuScenes [6] dataset resulting in STSnu, which comprises 971 multiple-choice questions derived from 43 diverse traffic scenarios. This benchmark provides a rigorous evaluation of driving expert models in terms of their spatio-temporal understanding from a holistic, scene-level perspective. Our evaluation revealed that, despite recent progress, current driving expert models still show significant limitations in spatio-temporal reasoning, highlighting the need for further research in this area.

Limitations. The major issue with publicly available large-scale driving datasets is that they mostly have clean and homogeneous data collection and filtering processes. For instance, nuScenes has been recorded in Boston and Singapore, and contains hardly unexpected or dangerous driving behavior. This is perfectly fine for perception tasks and also desirable from a human safety perspective. However, this is disadvantageous for the automatic mining of diverse traffic scenarios. Nevertheless, evaluations based on available data already pose significant challenges for driving expert models in terms of their spatio-temporal reasoning capabilities. Another bottleneck of automated scenario mining is the careful design of heuristics. For example, spatio-temporal processes have variable length. For instance, the time frame to detect *u-turns* is significantly longer than, for example, *lane changes*, especially when the agent has to interrupt the maneuver because of the current traffic situation. However, considering the rich annotations available, a simple set of heuristics can already provide sufficient preselection of traffic scenarios.

Social impact. Our work contributes to safe automated or autonomous driving systems: With STSnu, we highlight the lack of holistic scene understanding of state-of-the-art models. To mitigate the limitations (*e.g*. potential geographic bias, cannot test for safety-critical driving behavior due to lack of such data), we also open-source STSBench, a framework to easily extract and (most importantly) efficiently verify such benchmarks from other datasets. We explicitly rely on heuristics to ensure that the extracted benchmark scenarios are deterministic, easily reproducible and intuitive. We believe that our framework is a valuable and easy-to-use tool to guide future research on driving expert models towards better holistic scene understanding capabilities, in order to achieve safe and trustworthy systems.

Future work. With the growing interest in end-to-end autonomous driving and the corresponding expansion of the research community, an increasing number of high-quality datasets are becoming available. As perception models begin to reach saturation and deliver robust performance in standard driving conditions, research focus is shifting toward more challenging and rare situations. This trend opens up promising opportunities for extending STSBench to mine edge-case scenarios, such as accidents, wild animal crossings, or unexpected events, including cargo items (e.g., boxes, mats) falling from vehicles.

Beyond the inclusion of rare scenarios, STSBench can be extended along several additional dimensions. One direction is the modeling of finer-grained scenarios, incorporating risk attributes such as relative distances, agent velocities, or acceleration profiles to capture varying levels of criticality. Another extension involves multi-agent or event-chaining reasoning, where scenarios unfold across multiple entities and questions build upon one another. For example, a model might first identify the scenario as "overtaking" and then be asked: "Is this overtaking scenario dangerous?"

Once model performance begins to saturate on the current benchmark, which already poses a significant challenge to existing driving expert models, the benchmark can be extended to include a free-form answer track. This would challenge models to go beyond fixed-choice reasoning and offer richer explanations of driving situations, thereby providing a deeper assessment of their spatio-temporal understanding. In addition, more diversified question generation could be introduced to test the linguistic robustness of models and ensure that performance gains reflect true reasoning ability rather than sensitivity to phrasing.

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    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

    Answer: [NA]

    Justification: LLM usage did not not impact the core methodology, scientific rigorousness, or originality of the research.