Large Language Model-Informed Geometric Trajectory Embedding for Driving Scenario Retrieval

Tin Stribor Sohn[1,*], Maximilian Dillitzer[1,2,*], Tim Brühl[1], Robin Schwager[1], Tim Dieter Eberhardt[1], Michael Auerbach[2] and Eric Sax[3]

[1]*Dr. Ing. h.c. F. Porsche AG, Weissach, Germany*

[2]*Hochschule Esslingen, Esslingen, Germany*

[3]*Karlsruher Institut für Technologie, Karlsruhe, Germany*

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Abstract: This paper introduces a Large Language Model-informed geometric embedding for retrieving behavioural driving scenarios from unlabelled trajectory data, aimed at improving the search of real driving data for scenario-based testing. A Variational Recurrent Autoencoder with a Hausdorff Distance-based loss generates trajectory embeddings that capture detailed spatial patterns and interactions, offering enhanced interpretability over traditional mean squared error-based models. The embeddings are further organised through unsupervised clustering using HDBSCAN, grouping scenarios by similarities at the scene, infrastructure, behaviour, and interaction levels. Using GPT-4o for describing scenarios, clusters, and inter-cluster relationships, the approach enables targeted scenario retrieval via a Graph Retrieval-Augmented Generation pipeline, enabling a natural language search of unlabelled trajectories. Evaluation demonstrates a retrieval precision of 80.2% for behavioural queries involving infrastructure, multi-agent interactions, and diverse traffic conditions.

1 INTRODUCTION

The *Safety of the Intended Functionality* (SOTIF) standard provides guidance for the *validation and verification* (V&V) process of *automated driving systems* (ADS). According to SOTIF, driving functions must not only ensure safety under typical operating conditions, but must also be able to deal with hazardous and unforeseen scenarios that pose the highest safety risks (International Organization for Standardization, 2022). This standard emphasises the need for an ADS not only to behave safely on its own, but also to anticipate and handle potential faults and misbehaviour of other road users, emphasising that driving functions need to be evaluated at a behavioural level to ensure robust fault anticipation.

In real-world driving data, road user behaviour is often represented by object lists with associated trajectories that serve as indicators of driving scenarios. However, mapping scenarios and their associated trajectories to each other remains a significant challenge for V&V tasks. Existing manoeuvre-based

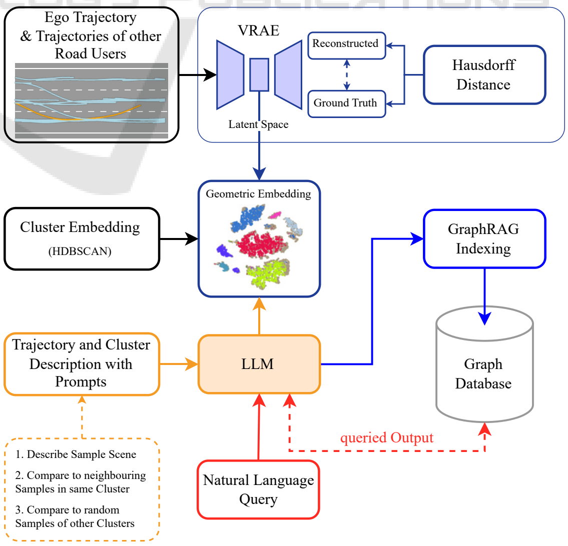

Figure 1: Method for generating geometric trajectory embeddings and mapping them to textual descriptions, enabling scenario retrieval and searchability at a behavioural level through natural language queries.

approaches often rely on pre-defined rules, which

*Equal contribution

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may not be sufficient to capture the full range of behavioural complexity.

This paper proposes a novel method to enhance the searchability of unlabelled trajectory-based scenarios found in naturalistic driving data through the integration of geometric trajectory embeddings and *Large Language Models* (LLMs) (Fig. 1). By addressing existing limitations in the searchability of behavioural scenarios in *scenario-based testing* (SBT), the proposed method contributes to the state of the art in five key ways:

- **Fine-Grained Clustering of Unlabelled Trajectories:** Using a variational recurrent autoencoder and a Hausdorff loss function, geometric embeddings are generated for unlabelled trajectories that capture fine-grained attributes rather than average metrics such as *mean squared error* (MSE). Cluster analysis within this embedding space is achieved by *Hierarchical Density-Based Spatial Clustering of Applications with Noise* (HDBSCAN) to reveal attribute patterns.
- **Integrated Embedding of Scene Elements and Interactions:** The joint geometric embedding encompasses infrastructure, general scene context, manoeuvres, and object interactions, reflecting multi-object scenarios.
- **Behavioural Scenario Description and Searchability:** By describing and comparing trajectory clusters in the geometric embedding through prompting an LLM for natural language descriptions (Wei et al., 2022), the method improves interpretability and enables behaviour-based searchability across clusters, allowing natural language queries to be mapped to trajectory data.
- **Indexing Through the GraphRAG Pipeline:** Embeddings are indexed within a Graph *Retrieval-Augmented Generation* (RAG) pipeline (Edge et al., 2024), enabling natural language retrieval and open vocabulary manoeuvre mapping, along with combinatorial behaviour scenario search.
- **Demonstrated Retrieval Performance:** Evaluation results indicate an average retrieval precision of 80.2% with promising results in scenarios retrieval involving infrastructure and object interactions, as well as in the combinatorial manoeuvre space.

2 RELATED WORK

Current behavioural scenario extraction methods can be classified into learning-based embeddings, trajectory clustering and rule-based manoeuvre extraction.

Learning-based trajectory embedding approaches use deep learning techniques to generate embeddings of driving scenarios.

Sonntag et al. introduced a method to minimise the test space by identifying edge cases using deep learning based outlier detection (Sonntag. et al., 2024). Their approach used autoencoders to generate trajectory embeddings and calculated MSE reconstruction errors to identify unusual scenarios. However, this method has limitations as it focuses primarily on spatio-temporal features and relies on an overall scenario embedding, which limits its applicability for detailed scenario analysis, particularly when addressing SOTIF. The use of MSE often fails to preserve the finer geometric properties of the trajectories, resulting in a more generalised representation that may miss critical behavioural nuances such as local lateral driving behaviour. In addition, the interpretability and searchability of the embedding is challenging as the properties of the clusters are not described.

Hoseini et al. present a non-parametric trajectory clustering framework using *Generative Adversarial Networks* (GANs) to generate realistic synthetic data (Hoseini et al., 2021). Their approach incorporates geometric relations through *Dynamic Time Warping* (DTW) and models transitive relations within an embedding space. However, its applicability to behavioural scenario search is limited due to the limited interpretability of the embedding space. Furthermore, it only considers lateral and longitudinal positioning, omitting key parameters essential for dynamic scenario characterisation, and focuses on only three specific scenarios: cut-in and left or right pass-by manoeuvres.

Clustering-based methods have also been explored to group similar driving scenarios, often focusing on the temporal and dynamic aspects of trajectories.

Ries et al. introduced a method for trajectory-based clustering using DTW, which identifies similar driving scenarios by comparing the temporal alignment of dynamic object trajectories (Ries et al., 2021). While this method is effective for querying similar trajectories, it does not capture the full complexity of driving scenarios, particularly in terms of abstraction layers that involve multiple interacting entities and related infrastructure.

Similarly, Watanabe et al. proposed a scenario clustering method based on predefined features (Watanabe et al., 2019). Although this approach allows for the organisation of scenario data, it lacks the ability to adaptively discover relevant features from the trajectory data itself, limiting its applicability to behavioural scenario search.

Rule-based manoeuvre extraction approaches for driving scenario retrieval are based on pre-defined rules and patterns.

Montanari et al. introduced a pattern clustering method that identifies recurring scenario patterns from time series data (Montanari et al., 2020). While this method is useful for recognising common scenarios and corner cases, it does not explicitly consider the geometric properties of the trajectories in relation to the infrastructure and lacks interpretability due to missing pattern descriptions.

Elspas et al. introduced a more sophisticated rule-based system using regular expressions to extract driving scenarios (Elspas et al., 2020). Their method focuses on detecting specific manoeuvres, such as cut-ins and lane changes, by applying pre-defined rules to time series data. While this allows for a functional interpretation of scenario patterns, the rule-based nature of the system requires significant manual effort to define appropriate patterns, which limits its scalability and adaptability to new scenarios, and may also lead to missing specifications of certain edge and corner cases.

Later, Elspas et al. used fully *Convolutional Neural Networks* (CNNs) to extract scenarios from time series data (Elspas et al., 2021). However, their approach relies on labelled datasets with ground truth annotations, which presents challenges in terms of complexity and scalability, as manually annotating large and diverse datasets is labour intensive and may not cover all relevant aspects of real-world behavioural driving scenarios.

Sohn et al. investigated natural language scenario retrieval, assessing the ability of different LLMs to capture scenario information (Sohn et al., 2024). However, as this work focused on the description and retrieval of perceptual data within the 6-Layer Model (6LM) framework (Scholtes et al., 2021), behavioural scenario retrieval was not a primary focus.

The methods reviewed address different aspects of trajectory embedding and scenario retrieval, but tend to either over-generalise or focus narrowly on specific aspects of driving behaviour. Learning-based methods tend to oversimplify trajectory embeddings by relying on MSE and overall scenario representations, which may obscure critical geometric and relational properties. Clustering methods focus primarily on temporal alignment and pre-defined features, but fail to capture the full complexity of multi-agent interactions. Rule-based methods, while useful for detecting specific manoeuvres, require significant manual effort and may struggle to adapt to new or complex scenarios. All presented methods lack searchability and interpretability of the derived clusters, leaving out the mapping of user queries or behavioural scenario descriptions to the trajectory space.

3 METHOD

To overcome these limitations, a novel method is proposed that aims to enhance the retrieval of driving scenarios by combining geometry-aware trajectory embeddings with word embeddings from LLMs, enabling behavioural-level searchability through natural language queries (Fig. 1). This approach is intended to support V&V processes for ADS, ensuring that behavioural patterns in unlabelled driving data can be effectively analysed and retrieved through natural language or behavioural scenario descriptions.

3.1 Fine-Grained Trajectory Embedding Using Geometric Loss

To generate a trajectory embedding that models the fine-grained geometric aspects of behavioural scenarios, a *Variational Recurrent Autoencoder* (VRAE) is employed using *Long Short-Term Memory* (LSTM) cells with self-attention to capture sequential patterns. The model is trained using the *Hausdorff Distance* (HD) as the loss function. Unlike the MSE, which tends to generalise trajectory features, the HD is able to preserve spatial properties by quantifying the largest deviation between trajectory points. This property is necessary to preserve the geometric attributes required for fine-grained analysis of driving behaviour, particularly in scenarios involving multiple agents and dynamic interactions such as cut-ins, overtaking manoeuvres or multiple lane changes.

The HD (d_H) between two trajectories $A = \{a_1, a_2, \dots, a_m\}$ and $B = \{b_1, b_2, \dots, b_n\}$ in a metric space with the Manhattan (L1) distance $d_M(a,b) = \sum_{i=1}^{d} |a_i - b_i|$ is defined as follows:

$$d_H(A,B) = \max\left\{\sup_{a\in A}\inf_{b\in B} d_M(a,b),\ \sup_{b\in B}\inf_{a\in A} d_M(a,b)\right\}$$

This metric ensures that each point in A is close to at least one point in B and vice versa, capturing trajectory similarity based on maximum deviation. Using HD as a loss function within the VRAE allows for a more accurate representation of trajectory structure, which is required for behavioural scenario analysis.

3.2 Clustering of Trajectory Embeddings with HDBSCAN

Following embedding generation, trajectories are clustered using *Hierarchical Density-Based Spatial Clustering of Applications with Noise* (HDBSCAN) (McInnes et al., 2017). It is well suited to dealing with the distinctive features of unlabelled, naturalistic trajectory data by identifying clusters of different densities based on spatial and behavioural characteristics from coarse to fine-grained properties. HDBSCAN helps to isolate clusters that reflect different driving behaviours, allowing further analysis at a scenario level. By explicitly accounting for noise in the data, it also helps to identify unique patterns that represent outliers. This clustering step thus organises the trajectory embeddings according to fine-grained attributes, preserving the distinctions between the different driving behaviours observed.

3.3 Semantic Interpretation of Scenarios Using LLMs

To make the generated embedding interpretable, each trajectory cluster and individual scenarios within the clusters are described using an LLM, in this approach GPT-4o (OpenAI, 2024). This is achieved using a prompt pipeline consisting of three main steps for each sample in the dataset:

1. A single scenario is given as context with the task to analyse overall properties such as traffic density and each of the object trajectories in relation to the infrastructure (road properties such as lanes) as well as the interaction with other objects.
2. The corresponding cluster in the embedding space is used to sample the five nearest neighbours of the sample within its cluster to describe the intrinsic attributes of the cluster by comparing the samples to each other.
3. Each of the other clusters is considered by sampling randomly five samples and describing them as well as comparing them with the previously described cluster.

Each description is referenced to the corresponding data samples and associated clusters. This ensures interpretability at sample level, within clusters and between clusters of behavioural scenarios, and allows user queries to search from coarse to fine-grained behavioural similarities and differences. This step facilitates the translation of raw geometric data into semantically meaningful interpretable representations, bridging the gap between abstract trajectory data and functional driving behaviour. The integration of LLMs improves searchability by linking trajectory embeddings to a descriptive language.

3.4 Natural Language Scenario Retrieval via GraphRAG Pipeline

The generated descriptions, combined with the corresponding references in the dataset and the clustered embedding, are indexed using a GraphRAG pipeline. The idea of RAG is to provide a queryable external context source for LLMs to answer targeted questions about specific data not previously used to train the LLM. GraphRAG implements this idea by modelling the data into a knowledge graph, addressing relationships between entities as well as general concepts by clustering the knowledge graph (Edge et al., 2024). By embedding the knowledge graph in the same embedding as the LLM queries, natural language search can be performed by referencing the previously generated descriptions as well as their associated data samples and trajectory embedding clusters.

4 EXPERIMENTS

4.1 Dataset

In this paper, a naturalistic vehicle trajectory dataset is used to support trajectory embedding generation and retrieval tasks.

The HighD dataset consists of more than 110,500 vehicles covering approximately 44,500 kilometres of driving over 147 hours. The data, focusing on highway scenarios, was collected with a drone at six different German highway locations, overcoming common limitations of traditional traffic data collection such as occlusion. The trajectory of each vehicle, including manoeuvres and dimensions, was extracted with a positioning error of less than ten centimetres (Krajewski et al., 2018). For analysis, within the frame of this research, the dataset is segmented into 15-second sequences to allow for the analysis of vehicle interactions and manoeuvres at a higher granularity.

4.2 Embedding Generation and Cluster Analysis of Driving Scenarios

To analyse the embedding, both MSE and HD are used as loss functions to generate the trajectory embedding with VRAE. The differences identified are compared by analysing the HDBSCAN clusters on a *t-distributed Stochastic Neighbour Embedding* (t-SNE) projection and mapping general properties such as *number of lanes*, *lane change*, *speed*, *acceleration*, and *traffic density* to the embedding.

These metrics not only provide insight into the specific behavioural characteristics of each cluster, but also help validate the plausibility of behavioural scenario representations, as clusters are expected to reflect infrastructure characteristics, ego-object dynamics, as well as manoeuvres and interaction patterns.

Both the description and the retrieval performance of the proposed approach are validated using a set of 33 different user queries related to behavioural scenario analysis (Table 1). Specifically, these queries are categorised as follows:

- **General Scene:** Retrieval of scenarios based on general properties such as traffic density or base infrastructure such as amount of lanes.
- **Infrastructure Manoeuvres:** Focused retrieval based on manoeuvre interactions with infrastructure elements such as lane markings (e.g. a lane change).
- **Ego Manoeuvres:** Retrieval based on trajectory characteristics and behaviour of the trajectory itself, which can be broken down into motion primitives such as speed and acceleration.
- **Object Interaction:** Retrieval focused on interactions between road users, capturing multi-agent dynamics.
- **Combinatorial Scenarios:** Retrieval based on combinations of general, infrastructure, ego manoeuvres and interactions, such as simultaneous high density traffic and lane change manoeuvres.

Scenario retrieval performance is assessed using the *Precision@k* (prec@k) metric, measured across different retrieval categories (General, Infrastructure, Ego, Interaction and Combinatorics). Specifically, the prec@k metric is used to determine the relevance of the top five retrieved samples for each query. The average prec@k value for all queries belonging to the same category is used for the analysis.

5 RESULTS

5.1 Analysis of Geometric Embedding

In order to evaluate the properties and feasibility of geometric embedding using HD, a comparison with an MSE-based embedding is performed.

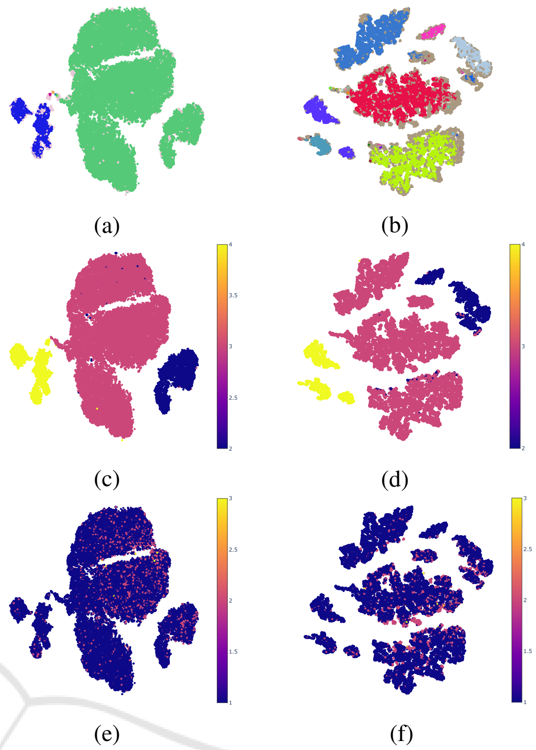


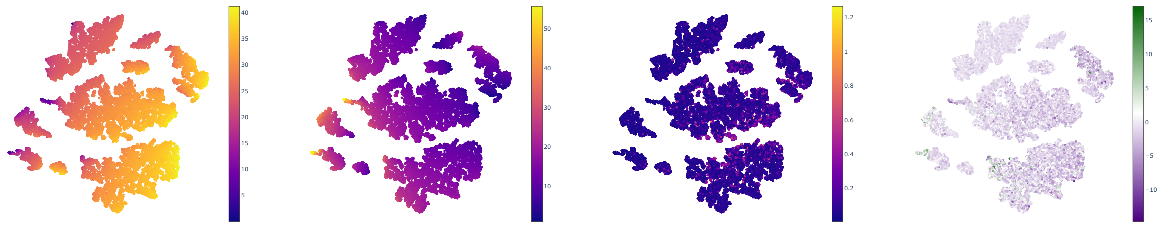
Figure 2: Trajectory embeddings using MSE (a) and HD (HD) (b), along with their corresponding embeddings of scenario features such as the number of lanes (c, d) and lane changes (e, f).

5.1.1 General Structure of the Embedding Space and Resulting HDBSCAN Clusters

The MSE and HD embeddings, along with their respective clustering results, show differences in cluster granularity, as seen in the clustering results produced by the HDBSCAN algorithm (Fig. 2a, 2b). The identified clusters show differences in coarseness between the embedding methods, with a notable difference in the number of clusters observed in each embedding type, which is 8 for MSE and 49 for HD.

5.1.2 Mapping of Behavioural Scenario Features to the Embedding Space

To illustrate the separability of features within clusters, two features are mapped: one general (number of lanes) and one trajectory-specific (lane change). In both embeddings, clusters representing different lane numbers are visually distinct (Fig. 2c, 2d). The mapping of lane changes shows different distributions, with the MSE embedding showing a randomly distributed pattern of samples, whereas the HD embedding shows these changes along the edges of visually separated clusters, as seen in the grey HDBSCAN cluster (Fig. 2e, 2f).



(a) (b) (c) (d)

Figure 3: HD embeddings of driving scenario features, including mean velocity in [m/s] (a), number of road users (b), lateral velocity change in [m/s²] (c) and longitudinal velocity change in [m/s²] (d).

Given these observations, while the MSE embeddings can be used to identify general attributes, the ability to identify fine-grained details of the trajectories is significantly compromised. Consequently, only the HD embedding is considered for the subsequent analysis.

5.2 Driving Scenario Features

To analyse the interpretability and searchability of the HD embedding, additional previously extracted features such as *mean velocity*, *number of objects*, *lateral velocity change* and *acceleration* are mapped onto the embedding visualisation. These features are also cross-referenced with the descriptions generated by the LLM for the corresponding clusters.

The mean velocity evaluation shows a clear gradient across the clusters, with low speed scenarios concentrated on the left and high speed conditions on the right (Fig. 3a).

The number of road users within a scenario further supports this division, as a higher density of road users appears on the left side of the visualisation (Fig. 3b). In particular, a dense cluster at the leftmost tip of the embedding, characterised by a high number of road users and low speed, suggests traffic congestion. This observation is consistent with the LLM descriptions, which highlight congestion and disrupted flow in this area. Conversely, the right side of the visualisation, characterised by fewer road users, correlates with high speed scenarios and continuous traffic flow.

Changes in lateral velocity are more pronounced at the periphery of the clusters (Fig. 3c), consistent with the HD embedding's identification of lane changes, particularly at the edges (Fig. 2f). The LLM descriptions support this by noting lane changes and multi-lane adjustments within the edges of the respective main clusters.

The longitudinal speed changes show the dynamics of acceleration and deceleration across the scenarios (Fig. 3d). Acceleration values are concentrated on the left side of the embedding, where lower

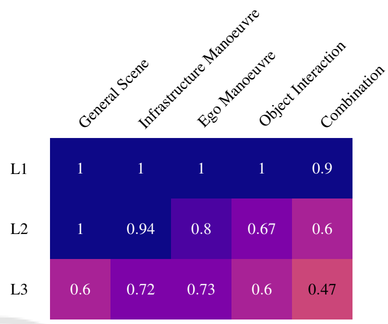


Figure 4: Retrieval performance of the LLM for behavioural queries and their combinatorics with three levels of detail (average prec@5 over several queries).

speeds dominate, allowing greater acceleration potential. Conversely, deceleration values are concentrated in the right-hand clusters, corresponding to the high-speed conditions. This inversion, where lower speeds allow greater acceleration and higher speeds involve greater deceleration, is consistent with typical driving behaviour, as confirmed by the LLM scenario descriptions, which capture this contrasting pattern between the low-speed, acceleration-rich areas and the high-speed, deceleration-dominant clusters.

5.3 Retrieval Analysis

For retrieval analysis, the LLM is queried at three levels of detail: L1, L2 and L3. Example queries are listed in Table 1. The query results are shown in Figure 4, where darker tiles indicate better model performance, with 0% being the lowest score and 100% being the best possible score. As the prec@k is calculated based on the top five retrieved samples, values up to 100% are possible for the average prec@k value of several queries.

The performance of the model varies with the complexity of the queries. At the lowest level of detail (L1), simple queries, such as keeping the speed of the ego trajectory constant, give an average prec@k of 98%. At the medium complexity level (L2), queries such as *" pass-by from left"* result in an average

Table 1: Overview of query types for trajectory retrieval: Categorisation of *General Scene*, *Infrastructure Manoeuvre*, *Ego Manoeuvre*, *Object Interaction* and *Combination* queries by level of complexity (L1, L2, L3). Text in *italic* denotes placeholders for specific values (e.g., *direction* = left, *speed value* = 20 km/h)

Description Objective	L1 Queries	L2 Queries	L3 Queries
General Scene	Retrieve trajectories of vehicles on a two-lane highway; three-lane highway scenario	Retrieve trajectories in moderate traffic density; congested traffic conditions	Retrieve trajectories with high traffic density in *lane_number*; heavy traffic in middle and left lanes with free traffic flow in right lane
Infrastructure Manoeuvre	Retrieve trajectories of vehicles maintaining lane *number*	Retrieve trajectories involving lane changes at speeds above *speed value*; performing aggressive lane changes	Retrieve trajectories showing lane change to the *direction*; multi-lane changes of different road users at the same time
Ego Manoeuvre	Retrieve trajectories of vehicles travelling at a constant speed of *speed value*	Retrieve trajectories with acceleration; deceleration; lateral movement without lane change	Retrieve stop-and-go trajectories; acceleration up to *speed value*; braking to below *speed value*
Object Interaction	Retrieve trajectories following an object at *speed value*; approaching an object at *speed value*	Retrieve trajectories with pass-by manoeuvre from the *direction*; cut-in at speeds above *speed value*	Retrieve trajectories with evasive manoeuvre; overtaking; merging into highway traffic in high density
Combination	Retrieve trajectories following a lane on a two-lane highway with high acceleration	Retrieve trajectories showing lane change after pass-by in moderate traffic	Retrieve trajectories with evasive manoeuvre to the right to lane *lane_number* at high speeds; multi-lane changes of one road user in heavy traffic

prec@k of 80.2%, indicating the ability to cover fine granularities in the description of behavioural scenarios. At the highest level of complexity (L3), queries such as *"evasive manoeuvre to the right at high speed"* are challenging and result in an average prec@k of 62.4%.

Overall, the *Infrastructure Manoeuvre* category achieves the highest performance across all levels, with an average prec@k of 88.7%. Conversely, the *Combination* category shows the lowest performance, with an average prec@k of 65.7%.

An extract of the detailed output from the LLM in response to a natural language query is shown in Table 2, which includes the exact query, the corresponding retrieved trajectory, and a condensed response from the LLM, shortened for total length.

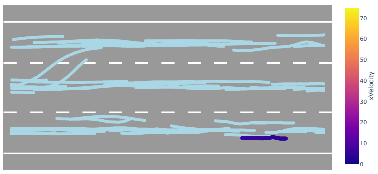
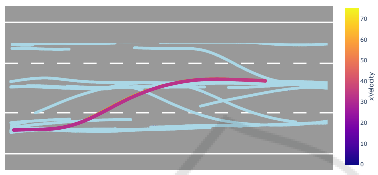
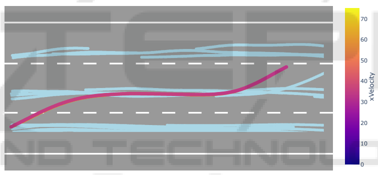
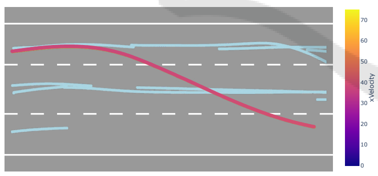
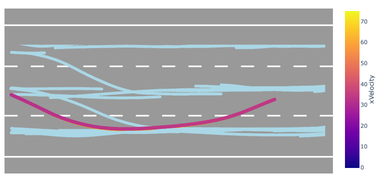
Qualitative analysis of these responses reveals the model's deep overall understanding of the objects involved and their relationships by querying the knowledge graph. The LLM provides detailed references within the knowledge graph, specifying information such as concrete object IDs and precise speed and acceleration values relevant to the queries. In particular, the model demonstrates high accuracy by providing the vehicle ID and specific time frames for each queried manoeuvre. In addition, the LLM output includes direct indices to data sources relevant to the query context, supporting traceability across data layers. Responses to complex queries remain clear and comprehensive, providing descriptions that capture both the sample retrieved and its contextual parameters.

6 EVALUATION

The embedding analysis results indicate that the HD embedding is highly effective for trajectory data. Compared to the MSE embedding, the HD embedding shows better performance in modelling and clustering trajectories, allowing for fine-grained differentiation of attributes such as lane change behaviour and specific ego manoeuvres. In contrast, MSE embedding primarily captures broader scenario characteristics and lacks the resolution to distinguish between detailed manoeuvres. Beyond the more distinct clusters, the applicability of the HD embedding is reinforced by consistent performance across different visualisations, such as the clear correlation between high-speed scenarios and low object counts, and vice versa. This geometric embedding approach facilitates the targeted search for behavioural scenarios and supports nuanced trajectory analysis. The generated LLM descriptions include the previously extracted features in their descriptions at the same locations in the same clusters as visualised in the embedding. This further demonstrates the feasibility of the three-stage cluster description by prompting an LLM for the purposes of interpretability and searchability.

Evaluating the retrieval performance, with an average prec@k of 80.2%, the presented approach shows that even higher levels of detail of the general scene, infrastructure, ego manoeuvres as well as object interactions can be described and retrieved. On the other hand, the high degree of combinatorics in the queries can be a challenge, with performance degrading towards higher levels of detail, affecting the overall performance.

Table 2: Detailed overview of trajectory retrieval queries: Examples of query types, corresponding top retrieved trajectories and shortened responses from the LLM, highlighting different driving manoeuvres and traffic conditions in real-world highway scenarios.

Query	Top Retrieved Trajectory	Shortened Answer of LLM
Retrieve trajectories in dense traffic on the right lane with low speed. (General Scene, L3)		In several highway scenarios, Lane 0, which is the rightmost lane, exhibits dense traffic with vehicles maintaining low speeds. Vehicles in Lane 0 generally show consistent following behavior, maintaining steady speeds and positions without significant lane changes or aggressive maneuvers. For instance, Vehicle ID 300 travels at below 9.3 m/s, maintaining a consistent lane-following behavior without significant speed variation [Data: Entities (981)]. Similarly, Vehicle 369 travels slower at around 15.3 m/s, slightly decelerating over time and maintaining its position in Lane 0, indicating moderate traffic density [Data: Entities (963)]. Additionally, Vehicle 678 follows a steady path with incremental velocities, further indicating a following behavior in Lane 0 [Data: Entities (193)]. These observations highlight the dense and low-speed traffic conditions in Lane 0, contributing to the overall traffic flow on the highway [Data: Reports (226); Entities (1480, 198, 347); Relationships (697, 743, 741, 1839, 2039)].
Retrieve trajectories of a lane change to the left. (Infrastructure Maneuver, L2)		Several vehicles in the dataset exhibit lane changes to the left, indicating maneuvers from a higher-numbered lane to a lower-numbered lane. Notable examples include: Vehicle ID 273: Changes from Lane 1 to Lane 2 at frame 2990, showing a leftward shift in trajectory [Data: Reports (147); Entities (1956); Relationships (663, 1583, 3782)]. Vehicle ID 2286: Moves from Lane 2 to Lane 1 at frame 27404, indicating a smooth, controlled transition [Data: Reports (147); Entities (304, 309); Relationships (2672, 128)]. Vehicle ID 2295: Lane change from Lane 1 to Lane 2 at frame 27488, demonstrating a smooth high-speed maneuver [Data: Reports (147); Entities (307, 310); Relationships (2674, 129)]. Vehicle ID 1383: Leftward shift from Lane 1 to Lane 2 around frame 16407[Data: Entities (630); Relationships (240)]. Vehicle ID 1176: Changes from Lane 1 to Lane 2 at frame 14070, possibly indicating an overtaking maneuver or adaptive lane positioning [Data: Entities (90); Relationships (1099)].
Retrieve trajectories of a multi lane change to the left. (Infrastructure Maneuver, L3)		Vehicle 210 initiates in Lane 2 and shifts to Lane 0 around frame 2321, with slight speed changes before and after the lane change, indicating a maneuver to overtake or evade slower traffic [Data: Entities (4); Relationships (15, 17, 663, 1583, 3782)]. Vehicle 2186 starts in lane 0 with a velocity around 31.9 m/s initially and changes to lane 2 around frame 2165, demonstrating a lane change maneuver without any significant speed variation [Data: Entities (1414); Relationships (478, 2763, 3955, 3962, 3969)]. Vehicle 273 changes lanes from Lane 2 to Lane 0 around frame 2990, indicated by a laneId change and a minor deviation in y-velocity [Data: Entities (1956); Relationships (663, 1583, 3782)]. Vehicle 1994 starts in lane 0 and transitions to lane 1 with a higher xVelocity around 33.58 and noticeable x-Velocity, indicating a lane change from 0 to 2, possibly for evasive maneuver [Data: Entities (1946); Relationships (4371, 2107, 2109)].
Retrieve trajectories of a aggressive lane change over multiple lanes to the right. (Infrastructure Maneuver, L3)		In the provided data, Vehicle 214 exhibits aggressive lane-changing behavior over multiple lanes to the right. Vehicle 214 maintains a high speed ranging from 35.65 to 37.17 m/s and shifts between Lanes 0, 1, and 2 over various frames, indicating multiple lane changes. These maneuvers suggest attempts to overtake other vehicles or adjust to varying traffic densities, reflecting a responsive and adaptive driving pattern [Data: Reports (261); Entities (6); Relationships (21, 20, 22, 24, 19, +more)].
Retrieve trajectories of an evasive maneuver to the right with a speed over 70 km/h. (Combination, L3)		The data provided indicates the presence of evasive maneuvers to the right by vehicles with speeds over 20 m/s. Within the highway scene, several vehicles exhibit high-speed driving with specific instances of abrupt lane changes or swerving actions that qualify as evasive maneuvers. For instance: Vehicle 214, and Vehicle 221 are noted for high-speed driving and dynamic lane-changing behaviors, which include evasive actions intended to avoid potential collisions. These maneuvers go beyond strategic overtaking or adaptive driving, as they involve rapid adjustments in trajectory to evade other vehicles. Additionally, the entity labeled "EVADE" confirms instances of evading within the dataset, specifically highlighting scenarios where evasive actions were observed. This entity references particular relationships and data points (Entities 32 and 867; Relationships 1810) that document recorded evasive maneuvers to the right by vehicles traveling over 20 m/s.

At the lowest levels of detail (L1 and L2), the LLM retrieves scenarios with high accuracy, and the descriptions it generates closely match the queried behaviours. This high accuracy indicates that the LLM effectively understands simple and moderately detailed scenarios, capturing key trajectory features and behavioural cues with little difficulty.

However, performance drops for the most complex queries (L3). This drop is most noticeable for queries that capture combined manoeuvres over longer periods of time, such as stop-and-go scenarios or long overtaking manoeuvres. One reason for this performance drop could be the segmentation of the data into 15 second sequences. As a result, these scenarios cannot be adequately queried as they are not properly embedded within this short time window. In these cases, the LLM reports that there are few or no such instances in the dataset, again demonstrating a good understanding but limiting its retrieval performance score for these queries. Choosing variable time windows to capture both short and long term manoeuvre development could help to capture these manoeuvres with the presented method. Additional performance challenges are particularly notable within the *Combination* category, which captures combinatorial queries of multiple behavioural elements. In many cases, the response contains specific subsets of the combinatorics, but often struggles to capture all related aspects for highly combinatorial queries at L2 and L3.

Qualitative analysis of the model responses shows a comprehensive understanding of the LLM in terms of the data samples and the associated clusters in the geometric embedding space. By providing both data and knowledge graph references, coupled with a full text answer and detailed reasoning about the retrieved scenarios, interpretability is facilitated.

7 CONCLUSION AND FUTURE WORK

This paper presents a comprehensive approach for retrieving behavioural scenarios on unlabelled trajectories from real driving data. The geometric embedding based on HD is able to capture detailed scenario attributes such as infrastructure, specific features of object trajectories as well as their interactions. The guided description of the trajectory space by GPT-4o combined with the indexing by a GraphRAG pipeline allows users to query and analyse the generated representation with natural language and behavioural scenario descriptions without prior annotation and additional information extraction. The open context nature of the LLM, by providing an open vocabulary, allows queries that do not necessarily need to be considered prior to data extraction.

Future research could focus on improving the proposed approach in several ways. First, the introduction of different segment lengths can be considered to accommodate different granularities in manoeuvre combinations, which would address potential performance issues, such as the observed challenges in stop-and-go scenarios as longer length takeovers. Subsequently, the use of alternative models to VRAE, such as Transformers, may also prove beneficial for extended context representation. This can be coupled with the inclusion of additional scenario parameters based on the 6LM for enhanced context representation and search. The database should be extended beyond the highway scenarios in the highD dataset, such as intersections, urban scenarios and other real-world use cases. To evaluate the scenario retrieval performance, ground truth datasets should be created that allow for additional performance metrics such as Recall@k. This can be combined with the evaluation of different alternative prompting and RAG approaches to improve retrieval specifically for combinatorial queries. Besides the HD which introduces a spatial distance, additional metrics should be evaluated with respect to the resulting embedding space for driving scenarios, specifically including temporal and spatial distances. Finally, the method should be evaluated and improved on the basis of user studies with the involvement of V&V engineers, investigating the most important types of queries as well as drawing the relation to the application related to the SOTIF standard.

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