

TRAJEVO: Trajectory Prediction Heuristics Design via LLM-driven Evolution

Zhikai Zhao^{1*}, Chuanbo Hua^{1, 2*}, Federico Berto^{1, 2*}, Kanghoon Lee¹, Zihan Ma¹,
Jiachen Li³, Jinkyoo Park^{1, 2}

¹KAIST, Korea Advanced Institute of Science and Technology, Daejeon, 34141, South Korea

²OMELET, Daejeon, South Korea

³University of California, Riverside, CA, USA

{zzk020202, cbhua, fberto, leehoon, zihanma}@kaist.ac.kr; jiachen.li@ucr.edu; jinkyoo.park@kaist.ac.kr

Abstract

Trajectory prediction is a critical task in modeling human behavior, especially in safety-critical domains such as social robotics and autonomous vehicle navigation. Traditional heuristics based on handcrafted rules often lack accuracy and generalizability. Although deep learning approaches offer improved performance, they typically suffer from high computational cost, limited explainability, and, importantly, poor generalization to out-of-distribution (OOD) scenarios. In this paper, we introduce TRAJEVO, a framework that leverages Large Language Models (LLMs) to automatically design trajectory prediction heuristics. TRAJEVO employs an evolutionary algorithm to generate and refine prediction heuristics from past trajectory data. We propose two key innovations: Cross-Generation Elite Sampling to encourage population diversity, and a Statistics Feedback Loop that enables the LLM to analyze and improve alternative predictions. Our evaluations demonstrate that TRAJEVO outperforms existing heuristic methods across multiple real-world datasets, and notably surpasses both heuristic and deep learning methods in generalizing to an unseen OOD real-world dataset. TRAJEVO marks a promising step toward the automated design of fast, explainable, and generalizable trajectory prediction heuristics. We release our source code to facilitate future research at <https://github.com/ai4co/trajevo>.

Introduction

Trajectory prediction is a cornerstone of intelligent autonomous systems (Madjid et al. 2025; Wang et al. 2025a,b), with numerous real-world applications, including autonomous driving (Wang et al. 2024a; Li et al. 2024b; Wang et al. 2025c; Lange et al. 2024; Wang et al. 2025d; Lange, Li, and Kochenderfer 2024), industrial safety (Robla-Gómez et al. 2017), robotic navigation (Vishwakarma et al. 2024; Li et al. 2024a; Yao et al. 2024), and planning (Li et al. 2022b, 2023b). The inherent stochasticity of these environments demands systems that can accurately process data with both temporal and spatial precision (Li et al. 2021; Nakamura, Tian, and Bajcsy 2024; Toyungernsub et al. 2024). For instance, in autonomous vehicle navigation, accurately predicting pedestrian trajectories is essential for avoiding collisions in complex urban settings (Cao et al. 2021; Li et al. 2023a; Choi et al. 2021). Similarly, in in-

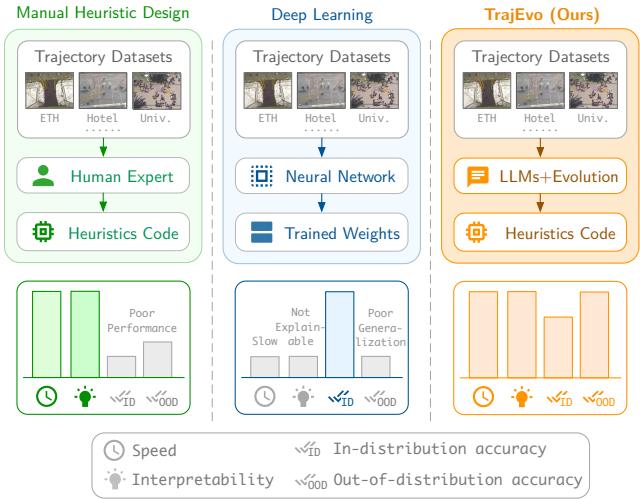


Figure 1: Motivation for our TRAJEVO framework. Traditional manual heuristic design (left) relies on human expertise and trial-and-error processes. Deep learning approaches (center) produce more accurate predictions but demand substantial computational resources, yield black-box models, and often struggle with generalization. TRAJEVO (right) automates the heuristic design process using evolutionary algorithms, enabling the generation of novel and effective trajectory prediction heuristics.

dustrial and indoor environments, robots must generate precise trajectory predictions to collaborate safely with humans in shared workspaces without causing harm (Mavrogiannis et al. 2023; Mahdi et al. 2022; Ma et al. 2022).

Accurately predicting the movement patterns of multiple agents, such as pedestrians or vehicles, remains fundamentally challenging. Human motion is inherently complex, characterized by nonlinear behaviors, sudden directional changes, and spontaneous decisions influenced by individual factors such as habits or urgency (Li et al. 2020; Xu et al. 2024). Moreover, agents interact dynamically, adjusting their paths to avoid collisions, responding to traffic, or moving cohesively in groups, which results in high stochasticity (Amirian et al. 2020; Zhou et al. 2022; Li et al. 2022a). Early efforts to model these behaviors relied on heuristic

*These authors contributed equally.

methods, including the Social Force model (Helbing and Molnar 1995), which captures interactions through physics-inspired forces (Helbing and Molnar 1995; Luber et al. 2010; Zanlungo, Ikeda, and Kanda 2011; Farina et al. 2017; Chen et al. 2018); constraint-based approaches that define collision-free velocities (van den Berg, Lin, and Manocha 2008; Ma, Manocha, and Wang 2018); and agent-based simulations of decision making processes (Yamaguchi et al. 2011). While these handcrafted heuristics offer interpretability, they are often difficult to tune for dynamic scenarios and tend to suffer from limited accuracy and generalization.

Deep learning methods have emerged as a powerful alternative to traditional heuristics (Alahi et al. 2016; Salzmann et al. 2020; Li et al. 2022a). Social-LSTM (Alahi et al. 2016) was among the earliest influential models, leveraging LSTMs for trajectory prediction. Since then, a wide range of approaches, such as graph neural networks (GNNs) (Rainbow, Men, and Shum 2021; Ma et al. 2021) and generative adversarial networks (GANs) (Gupta et al. 2018; Li, Ma, and Tomizuka 2019; Dendorfer, Elflein, and Leal-Taixé 2021), have been proposed to further improve prediction accuracy. More recently, Transformer-based frameworks (Kim et al. 2025; Bae, Lee, and Jeon 2024) and diffusion models (Yang et al. 2024; Gu et al. 2022; Fu et al. 2025) have shown promise in capturing complex dependencies in human motion patterns. However, deep learning methods suffer from several practical limitations. *a) Running Speed:* They often require significant computational resources and exhibit high latency, making them unsuitable for deployment on resource-constrained robots or vehicles (Itkina and Kochenderfer 2023; Jiang et al. 2025). *b) Interpretability:* As black-box models, they lack transparency, which hinders verification and reduces trust, especially in safety-critical applications (Dax et al. 2023; Liu et al. 2024c; Cai and Ren 2024). *c) Generalization Ability:* Perhaps most critically, they often generalize poorly in out-of-distribution (OOD) scenarios, potentially leading to unsafe behavior in unfamiliar environments (Korbmacher and Tordeux 2022; Rudenko et al. 2020). These challenges highlight the continued importance of robust and predictable heuristics in safety-critical systems (Phong et al. 2023), which requires methods that are not only accurate but also fast, explainable, and generalizable.

Therefore, we pose the following research question: *Can we automatically design computationally efficient, accurate, interpretable, and highly generalizable trajectory prediction heuristics?* Inspired by recent research exploring combinations of Large Language Models (LLMs) with Evolutionary Algorithms (EAs) for automated algorithm design (Dat, Doan, and Binh 2025; Ye et al. 2024; Chen et al. 2024; Liu et al. 2024a; Yuksekgonul et al. 2025; Liu et al. 2024b; Wu et al. 2024; Zhang et al. 2024; Zheng et al. 2025; Novikov et al. 2025), we propose a novel approach to automatically generate effective prediction heuristics. We hypothesize that coupling the generative and reasoning capabilities of LLMs with the structured search of EAs can overcome the limitations of manual heuristic design to discover novel, high-performance heuristics suitable for real-world deployment.

In this paper, we introduce TRAJEVO (**T**rajectory **E**volution), a novel framework designed to achieve this goal.

TRAJ EVO leverages LLMs within an evolutionary loop to iteratively generate, evaluate, and refine prediction heuristics directly from data. Our main contributions are as follows:

- We present TRAJ EVO, the first framework, to the best of our knowledge, that integrates LLMs with evolutionary algorithms specifically for the automated discovery and design of fast, explainable, and robust trajectory prediction heuristics for real-world applications.
- We introduce a Cross-Generation Elite Sampling strategy to maintain population diversity and a Statistics Feedback Loop that enables the LLM to analyze heuristic performance and guide the generation of improved candidates based on past trajectory data.
- We demonstrate that TRAJ E VO generates heuristics that significantly outperform prior heuristic methods on public-open real-world datasets and exhibit remarkable generalization, achieving an over 20% performance improvement on an unseen OOD dataset against both traditional heuristics and deep learning methods, while remaining computationally fast and interpretable.

Related Work

Heuristic Methods for Trajectory Prediction Traditional heuristic approaches provide interpretable frameworks for trajectory prediction, but often with accuracy limitations. The Constant Velocity Model (CVM) and its sampling variant (CVM-S) (Schöller et al. 2020) represent foundational baselines that assume uniform motion patterns. More sophisticated approaches include Constant Acceleration (Polychronopoulos et al. 2007), CTRV (Constant Turn Rate and Velocity) (Lu et al. 2021), and CSCRCR (Zhai, Meng, and Wang 2014), which incorporate different kinematic assumptions. The Social Force Model (Helbing and Molnar 1995) pioneered physics-inspired representations of pedestrian dynamics, with numerous extensions incorporating social behaviors (Zanlungo, Ikeda, and Kanda 2011; Farina et al. 2017; Chen et al. 2018) and group dynamics (Helbing, Farkas, and Vicsek 1997). Despite their efficiency and explainability, they typically struggle with complex real-world, multi-agent interactions due to their limited expressiveness and reliance on manually defined parameters – limitations our proposed TRAJ E VO framework specifically addresses through automatic heuristic generation.

Learning-based Trajectory Prediction Deep learning has substantially advanced trajectory prediction accuracy at the cost of computational efficiency and interpretability (Sun et al. 2022; Xie, Li, and Wang 2023). Social-LSTM (Alahi et al. 2016) is a seminal work using a social pooling mechanism to model inter-agent interactions, while Social-GAN (Gupta et al. 2018) leveraged generative approaches to capture trajectory multimodality. Graph-based architectures like STGAT (Huang et al. 2019) and Social-STGCNN (Mohamed et al. 2020) explicitly model the dynamic social graph between pedestrians. Recent approaches include Trajectron++ (Salzmann et al. 2020), which integrates various contextual factors, MemoNet (Xu et al. 2022) with its memory mechanisms, EigenTrajectory (Bae, Oh, and Jeon

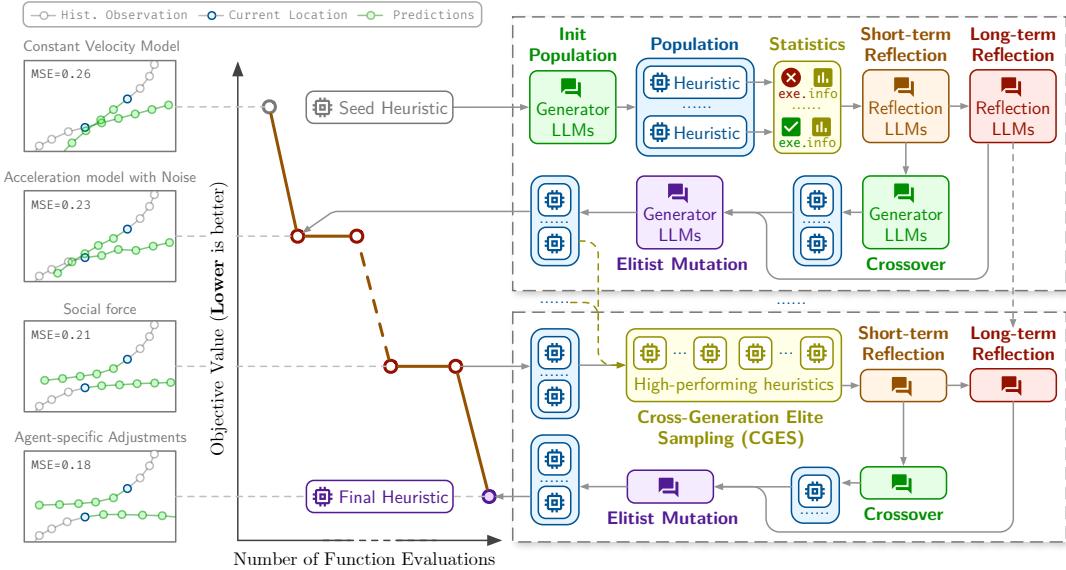


Figure 2: An illustration of the TRAJEVO evolutionary process. (**Left**) The framework continuously discovers and evaluates a variety of heuristic strategies, such as those based on constant velocity or social forces. (**Middle**) As the evolution progresses, the performance of these heuristics steadily improves, evidenced by the decreasing objective value from a simple seed to a final, optimized solution. (**Right**) The overall TRAJEVO pipeline orchestrates this entire discovery and optimization process, using an LLM-driven evolutionary algorithm to automatically generate and refine the heuristics.

2023) focusing on principal motion patterns, Hyper-STTN (Wang et al. 2024b) utilizing hypergraph-based spatial-temporal transformers for group-aware trajectory prediction, and MoFlow (Fu et al. 2025) employing normalizing flows for stochastic prediction. While these methods achieve high in-distribution accuracy, their three well-documented challenges: high computational cost, lack of interpretability, and poor out-of-distribution generalization (Rudenko et al. 2020), motivate the design of our TRAJEVO framework.

LLMs for Algorithmic Design Recent work has combined Large Language Models (LLMs) with Evolutionary Algorithms (EAs) for automated algorithm design (Ye et al. 2024; Dat, Doan, and Binh 2025). However, applying this paradigm to the safety-critical and stochastic domain of trajectory prediction remains unexplored. To the best of our knowledge, TRAJEVO is the first framework to adapt LLM-driven EAs for discovering fast, interpretable, and generalizable trajectory prediction heuristics. While these studies establish the general potential of LLM-driven evolution, its application to specialized, safety-critical domains remains largely unexplored. The domain of multi-agent trajectory prediction presents unique challenges, including stochastic interactions and the need for both high accuracy and computational efficiency. To the best of our knowledge, TRAJEVO is the first framework to adapt the LLM-driven evolutionary paradigm specifically for this task.

TRAJEVO

Problem Definition

Task We address multi-agent trajectory prediction. The task is, for each agent i , to predict its future path $Y_i =$

$(P_i^{T_{\text{obs}}+1}, \dots, P_i^{T_{\text{obs}}+T_{\text{pred}}})$ given its observed history $H_i = (P_i^1, \dots, P_i^{T_{\text{obs}}})$, where $P_i^t \in \mathbb{R}^2$ is the position at timestep t . Here, T_{obs} is the historical observation span and T_{pred} is the future prediction length.

Metrics We adopt the widely used standard measurement matrix in trajectory prediction to ensure fair comparison with all baselines (Gupta et al. 2018). Performance is measured by the minimum Average Displacement Error (minADE_K) and minimum Final Displacement Error (minFDE_K). This matrix evaluates a model’s ability to capture the multi-modal nature of human motion by generating K trajectory samples and selecting the one with the lowest error against the ground truth. Following the same setting as the baselines, we use $K = 20$ for our method to ensure a fair and direct comparison.

Optimization Objective To guide the evolutionary search, we employ the Mean Squared Error (MSE) and calculate the average squared Euclidean distance between the predicted and ground truth trajectory points, where a lower MSE corresponds to a higher fitness. The choice of MSE is motivated by its simplicity and generality, as well as its capacity to provide a continuous and well-defined error signal, which is crucial for guiding the evolutionary process. Its widespread adoption ensures our results are comparable across the literature, while its parameter-free nature aligns with our goal of automated heuristic design.

Evolutionary Framework

Our evolutionary framework is designed not merely to minimize prediction error on a given dataset, but to discover heuristics that are fundamentally simple and robust enough

to generalize across different environments. Inspired by the Reflective Evolution approach (Ye et al. 2024), the framework is illustrated in Fig. 2 (right). In this algorithm, Large Language Models (LLMs) serve as the core genetic operators, following these steps:

Initial Population The process starts by seeding the generator LLM with a task specification (including problem details, input/output format, and the objective J) alongside a basic heuristic like the Constant Velocity Model (CVM) (Schöller et al. 2020). The LLM then generates an initial population of N diverse heuristics, providing the starting point for the evolutionary search.

Selection for Crossover Parents for crossover are chosen from successfully executed heuristics in the current population. The selection balances exploration and exploitation: 70% of parents are selected uniformly at random from successfully running candidates, while 30% are chosen from the elite performers (those with the lowest objective J).

Reflections TRAJEVO employs two types of reflection as in Ye et al. (2024). *Short-term reflections* compare the performance of selected crossover parents, offering immediate feedback to guide the generation of offspring. *Long-term reflections* accumulate insights across generations, identifying effective design patterns and principles to steer mutation and broader exploration. Both reflection mechanisms produce textual guidance (i.e. “verbal gradients” (Pryzant et al. 2023)) for the generator LLM.

Crossover This operator creates new offspring by combining code from two parent heuristics. Guided by short-term reflections that compare the ‘better’ and ‘worse’ performing parent, the LLM is prompted to mix their effective “genes”, enabling the emergence of potentially superior heuristics.

Elitist Mutation The mutation operator mutates the elitist (best found so far) heuristic. In TRAJEVO, this involves the generator LLM modifying an elite heuristic selected. This mutation step is informed by the insights gathered through long-term reflections.

It is crucial to note that this entire evolutionary process is a one-time, offline procedure. The final output is a standalone Python heuristic that runs with high computational efficiency and does not require the LLM during inference.

Cross-Generation Elite Sampling

Evolving effective heuristics for complex tasks like trajectory prediction poses a significant search challenge, where standard evolutionary processes can easily get trapped in local optima (Osuna and Sudholt 2018). Simple mutations often yield only incremental improvements, failing to explore sufficiently diverse or novel strategies. To address this limitation and enhance exploration, we introduce Cross-Generation Elite Sampling (CGES), a core component influencing the mutation step within the TRAJEVO framework.

In contrast to typical elitism focusing on the current generation’s best, CGES maintains a history archive of high-performing heuristics accumulated across all past generations. Specifically, CGES modifies how the elite individ-

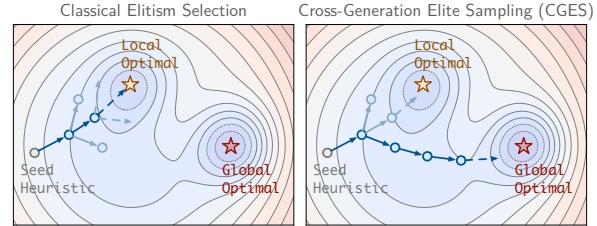


Figure 3: Cross-Generation Elite Sampling (CGES) helps escape local optima by sampling elite individuals from past generations (left), which greatly helps achieve much better objective values (right).

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...
<stats>
Statistics of trajectory index counts with
the lowest ADE. These help us understand
which heuristics contribute to the
performance for at least some trajectories.
Traj Index: Count: {0: 67, 1: 10, 2: 3, 3:
2, 4: 7, 5: 0, ... 18: 0, 19: 2}
</stats>
...
```

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...
The better code explicitly includes a
deterministic (linear extrapolation)
trajectory as the first prediction. This
significantly improves ADE, as evidenced by
trajectory 0 having the lowest ADE count by
far. The statistics suggest it's beneficial
to have at least one trajectory that closely
follows the established motion.
...
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Figure 4: Statistics Feedback Loop: (top) distribution of prediction index effectiveness by minimum ADE frequency; (bottom) LLM prompt incorporating statistical feedback for guided mutation.

ual targeted for mutation is selected: instead of necessarily choosing the top performer from the current population, the heuristic designated to undergo mutation is sampled by CGES directly from this history. This sampling uses a Softmax distribution based on the recorded objectives J of the historical elites, thus prioritizing individuals that have proven effective. By potentially reintroducing and modifying diverse, historically successful strategies during the mutation phase, CGES significantly improves the exploration capability, facilitating escape from local optima and the discovery of more robust heuristics, as demonstrated in Fig. 3.

Statistics Feedback Loop

While the objective J measures overall quality, it does not reveal *which* of a heuristic’s diverse internal prediction strategies are actually effective. To provide this crucial insight for effective refinement, TRAJEVO incorporates a Statistics Feedback Loop (SFL), illustrated in Fig. 4.

This loop specifically analyzes the contribution of the 20

distinct trajectory prediction sets (indexed $k = 0 \dots 19$) generated by a heuristic. After evaluation, we compute a key statistic: a distribution showing how frequently each prediction index k delivered the minimum ADE for individual trajectory instances across the dataset (Fig. 4 top). This directly highlights the empirical utility of the different diversification strategies associated with each index k . This statistical distribution, together with the heuristic’s code, is fed to the reflector and mutation LLMs to identify which strategies (k) contribute most effectively to performance (Fig. 4 bottom). Such feedback provides actionable guidance to the generator LLM, enabling specific improvements to the heuristic’s multi-prediction generation logic based on the observed effectiveness of its constituent strategies. A qualitative example of the full TRAJEVO evolution is provided in Fig. 2.

Experiments

Experimental Setup

Datasets We evaluate TRAJEVO on the ETH-UCY benchmark (Pellegrini et al. 2009; Lerner, Chrysanthou, and Lischinski 2007), a collection of datasets comprising real-world pedestrian trajectories with the standard leave-one-out protocol where heuristics are evolved on four datasets and tested on the remaining one (Alahi et al. 2016). To specifically assess OOD generalization, we use the SDD dataset (Robicquet et al. 2016) as a completely unseen test set. For all experiments, following the standard setting widely used by baseline methods on these benchmarks, we observe 8 past frames (3.2s) to predict 12 future frames (4.8s).

Baselines We compare heuristics generated by TRAJEVO against both heuristic and deep learning baselines. *Heuristic baselines*, which are well-suited for resource-constrained systems, include kinematic models such as the Constant Velocity Model (CVM) and its sampling variant (CVM-S) (Schöller et al. 2020), Constant Acceleration (ConstantAcc) (Polychronopoulos et al. 2007), and Constant Turn Rate and Velocity (CTRV) (Lu et al. 2021), as well as CSCRCTR (Zhai, Meng, and Wang 2014), Linear Regression (LinReg) (Bishop and Nasrabadi 2006), and the physics-inspired Social Force model (Helbing and Molnar 1995). To benchmark against more complex data-driven approaches, we also evaluate *deep learning baselines*, including early influential models like Social-LSTM (Alahi et al. 2016) and Social-GAN (Gupta et al. 2018); graph-based methods such as STGAT and Social-STGCNN (Mohamed et al. 2020); and recent state-of-the-art models like Trajectron++ (Salzmann et al. 2020), MemoNet (Xu et al. 2022), EigenTrajectory (Bae, Oh, and Jeon 2023), and MoFlow (Fu et al. 2025). To ensure robustness, all reported results for TRAJEVO are averaged over 10 independent evolutionary runs. The standard deviations across runs were consistently low, typically ranging from 0.02 to 0.06.

Hardware and Software All experiments were conducted on a workstation equipped with an AMD Ryzen 9 7950X 16-Core Processor and a single NVIDIA RTX 3090 GPU. The TRAJEVO framework generates trajectory prediction heuristics as executable Python code snippets in a Python 3.12

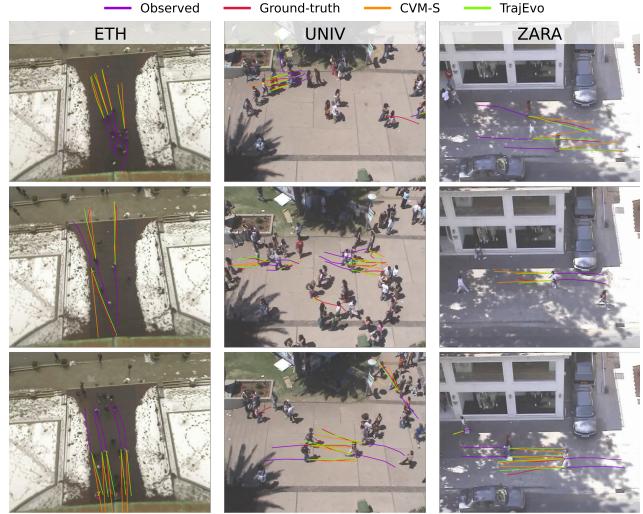


Figure 5: Trajectory prediction results for CVM-S (Schöller et al. 2020) and TRAJEVO across different datasets. Each row illustrates a distinct pattern: (top) linear trajectories, (middle) non-linear trajectories, and (bottom) collision-avoidance cases. We visualize the single best trajectory out of $K = 20$ samples based on the optimization objective.

environment, employing Google’s Gemini 2.0 Flash model (Google AI for Developers 2025) in the main experiment. To evaluate the stability and generalizability of our framework, its performance was systematically tested with a variety of alternative models, including DeepSeek V3 & R1, Qwen3-32B, ChatGPT-4o, and Claude 3.7 Sonnet.

In-Distribution Performance

Comparison with Heuristic Methods We report results against heuristic baselines in Table 1. TRAJEVO consistently achieves the best performance across all ETH-UCY datasets and significantly outperforms all competitors on average. This establishes TRAJEVO as the new state-of-the-art among heuristic approaches on this benchmark. Interestingly, the general performance trend across baseline methods suggests that heuristics incorporating more complexity beyond basic constant velocity assumptions are generally worse suited for real-world pedestrian data, including SocialForce, with the second-best result obtained by the relatively simple CVM-S. Fig. 5 shows examples of the generated trajectories.

Comparison with Deep Learning Methods Table 2 reports results against deep learning methods. On this in-distribution benchmark, while TRAJEVO does not surpass highly specialized neural networks like MoFlow (Fu et al. 2025), it establishes a strong baseline. It consistently outperforms several established models, including Social-LSTM (Alahi et al. 2016), and even more recent ones like Trajectron++ (Salzmann et al. 2020) on certain datasets. This performance is highly competitive for a heuristic-based approach. However, as the next section demonstrates, the primary strength of our method lies not in incremental in-distribution gains, but in its superior generalization capability.

Method	ETH	HOTEL	UNIV	ZARA1	ZARA2	Avg
SocialForce (Helbing and Molnar 1995)	1.46/2.48	0.69/1.23	0.96/1.75	1.37/2.51	0.84/1.53	1.06/1.90
LinReg (Bishop and Nasrabadi 2006)	1.04/2.20	0.26/0.47	0.76/1.48	0.62/1.22	0.47/0.93	0.63/1.26
ConstantAcc (Polychronopoulos et al. 2007)	3.12/7.98	1.64/4.19	1.02/2.60	0.81/2.05	0.60/1.53	1.44/3.67
CSCCTR (Zhai, Meng, and Wang 2014)	2.27/4.61	1.03/2.18	1.35/3.12	0.96/2.12	0.90/2.10	1.30/2.83
CVM (Schöller et al. 2020)	1.01/2.24	0.32/0.61	0.54/1.21	0.42/0.95	0.33/0.75	0.52/1.15
CVM-S (Schöller et al. 2020)	0.92/2.01	0.27/0.51	0.53/1.17	0.37/0.77	0.28/0.63	0.47/1.02
CTRV (Lu et al. 2021)	1.62/3.64	0.72/1.09	0.71/1.59	0.65/1.50	0.48/1.10	0.84/1.78
TRAJEVO	0.47/0.77	0.17/0.30	0.51/1.10	0.35/0.75	0.27/0.57	0.35/0.70

Table 1: Comparison of TRAJEVO with trajectory prediction heuristics across datasets with mean minADE_{20} / minFDE_{20} (meters) on the ETH-UCY dataset.

Method	ETH	HOTEL	UNIV	ZARA1	ZARA2	Avg
Social-LSTM (Alahi et al. 2016)	1.09/2.35	0.79/1.76	0.67/1.40	0.56/1.17	0.72/1.54	0.77/1.64
Social-GAN (Gupta et al. 2018)	0.87/1.62	0.67/1.37	0.76/1.52	0.35/0.68	0.42/0.84	0.61/1.21
STGAT (Huang et al. 2019)	0.65/1.12	0.35/0.66	0.52/1.10	0.34/0.69	0.29/0.60	0.43/0.83
Social-STGCNN (Mohamed et al. 2020)	0.64/1.11	0.49/0.85	0.44/0.79	0.34/0.53	0.30/0.48	0.44/0.75
Trajectron++ (Salzmann et al. 2020)	0.61/1.03	0.20/0.28	0.30/0.55	0.24/0.41	0.18/0.32	0.31/0.52
MemoNet (Xu et al. 2022)	0.41/0.61	0.11/0.17	0.24/0.43	0.18/0.32	0.14/0.24	0.21/0.35
EigenTrajectory (Bae, Oh, and Jeon 2023)	0.36/0.53	0.12/0.19	0.24/0.43	0.19/0.33	0.14/0.24	0.21/0.34
MoFlow (Fu et al. 2025)	0.40/0.57	0.11/0.17	0.23/0.39	0.15/0.26	0.12/0.22	0.20/0.32
TRAJEVO	0.47/0.77	0.17/0.30	0.51/1.10	0.35/0.75	0.27/0.57	0.35/0.70

Table 2: Comparison of TRAJEVO with deep learning approaches (mean $\text{minADE}_{20}/\text{minFDE}_{20}$ on ETH-UCY). Each underlined number indicates that the result is worse than the corresponding result from TRAJEVO on at least one metric.

ties in OOD situations.

Out-of-Distribution Performance

A crucial capability for robotic systems deployed in the real world is generalizing to unseen (OOD) environments during development. We evaluate this on the unseen dataset SDD, directly testing both deep learning models (trained on ETH-UCY) and the heuristics from TRAJEVO (evolved on the ETH-UCY). We report these OOD performance results in Table 3 for three selected heuristics and three recent established neural methods. Remarkably, TRAJEVO demonstrates superior generalization, significantly outperforming not only all heuristic baselines but also all tested deep learning methods, including SOTA models like MoFlow (Fu et al. 2025). TRAJEVO performs substantially better than the best deep learning competitor, EigenTrajectory (Bae, Oh, and Jeon 2023) and MoFlow. This suggests that the interpretable and efficient heuristics discovered by TRAJEVO may possess greater robustness to domain shifts compared to complex neural networks trained on specific distributions. For a bidirectional validation of generalization ability, we provide the reverse experiment in the Appendix.

Ablation Study

We conducted an ablation study, reported in Table 4, to validate the effectiveness of the core components introduced in TRAJEVO. The results demonstrate that both the SFL and CGES meaningfully improve performance. Removing either component from the full framework leads to a noticeable degradation in prediction accuracy, confirming their positive

contribution. The significant impact of CGES on enhancing the quality of generated heuristics during evolution is further visualized in Appendix Fig. 10.

Analysis and Discussion

Performance of Different LLMs To demonstrate the robustness of the TRAJEVO framework and the stability of its outcomes, we evaluated its performance when driven by several state-of-the-art LLMs, including DeepSeek-V3 & R1, Qwen3-32B, ChatGPT-4o, and Claude 3.7 Sonnet. As detailed in Table 5, a key finding is the consistent effectiveness across all models. Each LLM was capable of generating high-performing heuristics, which underscores the general utility and stability of TRAJEVO. While the overall performance level remained high and stable, we did observe minor variations that highlight opportunities for fine-tuning. For instance, Deepseek-R1 achieved the best average results, while other models excelled on specific datasets. This analysis confirms that the TRAJEVO framework is effective and not reliant on a single specific LLM, ensuring stable, high-quality outcomes regardless of the chosen model.

Evolution Resources A single TRAJEVO evolutionary run takes approximately 5 minutes using Google’s Gemini 2.0 Flash (Google AI for Developers 2025) with an average API cost of \$0.05. In contrast, training neural methods can take a full day on a contemporary GPU, incurring significantly higher estimated compute costs – e.g., on an RTX 3090 as reported by Bae, Oh, and Jeon (2023), around \$4 based on typical rental rates, 80× more than TRAJEVO.

Method (tested on SDD dataset)	ETH	HOTEL	UNIV	ZARA1	ZARA2	Avg
SocialForce (Helbing and Molnar 1995)	33.64/60.63	33.64/60.63	33.64/60.63	33.64/60.63	33.64/60.63	33.64/60.63
CVM (Schöller et al. 2020)	18.82/37.95	18.82/37.95	18.82/37.95	18.82/37.95	18.82/37.95	18.82/37.95
CVM-S (Schöller et al. 2020)	16.28/31.84	16.28/31.84	16.28/31.84	16.28/31.84	16.28/31.84	16.28/31.84
Trajectron++ (Salzmann et al. 2020)	46.72/69.11	47.30/67.76	46.08/75.90	47.30/72.19	46.78/68.59	46.84/70.71
EigenTrajectory (Bae, Oh, and Jeon 2023)	14.51/25.13	14.69/24.64	14.31/27.60	14.69/26.25	14.53/24.94	14.55/25.71
MoFlow (Fu et al. 2025)	17.00/27.98	17.21/27.43	17.00/30.63	17.24/29.22	17.27/27.56	17.14/28.56
TRAJEVO	12.58/23.82	12.26/23.60	12.78/23.71	13.10/25.23	12.22/23.57	12.59/23.99

Table 3: Out of distribution performance of methods trained on different ETH-UCY splits and tested on the unseen SDD dataset. We report minADE₂₀ / minFDE₂₀ (pixels) on the SDD dataset.

Dataset	- SFL - CGES	- SFL	TRAJEVO
ETH	0.68/1.36	0.59/1.12	0.47/0.77
HOTEL	0.26/0.45	0.19/0.33	0.17/0.30
UNIV	0.59/1.22	0.52/1.13	0.51/1.10
ZARA1	0.37/0.77	0.36/0.76	0.35/0.75
ZARA2	0.31/0.65	0.28/0.59	0.27/0.57

Table 4: Ablation study for the evolution framework removing different components. Lower is better (↓).

Model	ETH		HOTEL		UNIV	
	ADE	FDE	ADE	FDE	ADE	FDE
deepseek-R1	0.46	0.74	0.16	0.29	0.49	1.06
deepseek-V3	0.43	0.71	0.21	0.39	0.50	1.08
Qwen3-32B	0.49	0.74	0.18	0.32	0.51	1.09
ChatGPT-4o	0.51	0.82	0.15	0.30	0.54	1.13
Claude-3.7	0.49	0.93	0.18	0.36	0.49	1.07

Model	ZARA1		ZARA2		Avg	
	ADE	FDE	ADE	FDE	ADE	FDE
deepseek-R1	0.33	0.72	0.26	0.54	0.34	0.67
deepseek-V3	0.34	0.69	0.27	0.56	0.35	0.69
Qwen3-32B	0.35	0.75	0.27	0.59	0.36	0.70
GPT-4o	0.36	0.72	0.31	0.54	0.37	0.70
Claude-3.7	0.32	0.61	0.27	0.57	0.35	0.71

Table 5: Performance of various LLMs on the standard ETH-UCY benchmark datasets. Best results are in bold.

Inference Resources Crucially, the LLM is only used during the offline evolutionary design phase and is not called at inference time. The resulting heuristics are lightweight Python functions. As such, TRAJEVO-generated heuristics demonstrate significant speed advantages, requiring only 0.65ms per instance on a single CPU core with the Python version and less than 5 μ s for a version of the heuristic rewritten in C++. In contrast, neural baselines need 12-29ms on GPU and 248-375ms on (multi-core) CPU. Notably, TRAJEVO achieves over 10 \times speedup for the original Python version and more than 2400 \times speedup for the C++ version compared to the optimized MoFlow running on a dedicated GPU, highlighting its relevance for resource-constrained, real-time robotic systems.

Explainability Unlike the black-box nature of neural networks, TRAJEVO produces human-readable Python code. For instance, the heuristic evolved for the Zara1 dataset (see Supplementary Material for the full code) is not a simple tweak of a known model. It intelligently combines four distinct strategies to generate its 20 samples. The primary strategy ($k = 0..9$) is a sophisticated form of adaptive linear extrapolation, where the velocity vector is averaged over the last few steps and perturbed by noise scaled to the agent’s current speed—allowing it to model both smooth paths and sudden hesitations. A second strategy ($k = 10..14$) introduces rotational noise, effectively simulating curved paths. A third ($k = 15..17$) implements a memory-based collision avoidance mechanism by checking potential future positions against the recent paths of nearby agents. The final strategy ($k = 18, 19$) acts as a conservative fallback, using a heavily damped extrapolation. This automated discovery of a complex, multi-faceted strategy combining adaptive kinematics and interaction rules is a key advantage, making the model’s logic transparent and verifiable, which is crucial for safety-critical applications.

Conclusion

We introduced TRAJEVO, a novel framework leveraging Large Language Models and evolutionary algorithms to automate the design of trajectory prediction heuristics. Our experiments demonstrate that TRAJEVO generates heuristics which not only outperform traditional methods on standard benchmarks but also exhibit superior out-of-distribution generalization performance, remarkably surpassing even deep learning models on unseen data while remaining fast and interpretable. We believe TRAJEVO represents a significant first step towards automatically discovering efficient, explainable, and generalizable trajectory prediction heuristics, offering a practical and powerful alternative to conventional black-box models.

Future research will focus on bridging the performance gap to state-of-the-art models by enhancing the sophistication of the evolutionary search and incorporating multimodal contextual inputs. To ensure greater real-world applicability, the optimization objective will be reframed from single metrics of predictive accuracy towards holistic performance on downstream tasks like navigation and planning.

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Supplementary Materials

Qualitative Example of the Evolutionary Process

The evolutionary process of TRAJEVO is qualitatively illustrated in Figure 6. The optimization begins with a simple **Seed Heuristic**, which has a relatively high initial objective value (lower is better). Guided by the LLM, TRAJEVO then explores the solution space by generating and testing diverse new heuristics.

As shown in the figure, this exploration phase involves testing various distinct strategies, such as adding noise to an acceleration model (**Acceleration model with Noise**), simulating social forces (**Constant Velocity with Repulsion**), or averaging velocity over time (**Weighted Average Velocity**). Through mechanisms like the Statistics Feedback Loop and Cross-Generation Elite Sampling, the system identifies and refines the most effective of these strategies.

The process ultimately converges on a highly optimized **Final Heuristic**. This final algorithm is not a single, simple model but a complex combination of the most successful traits discovered during evolution, such as a drift towards the mean position and other agent-specific adjustments. This demonstrates the ability of TRAJEVO to automate the design of a sophisticated, high-performance heuristic from a basic starting point.

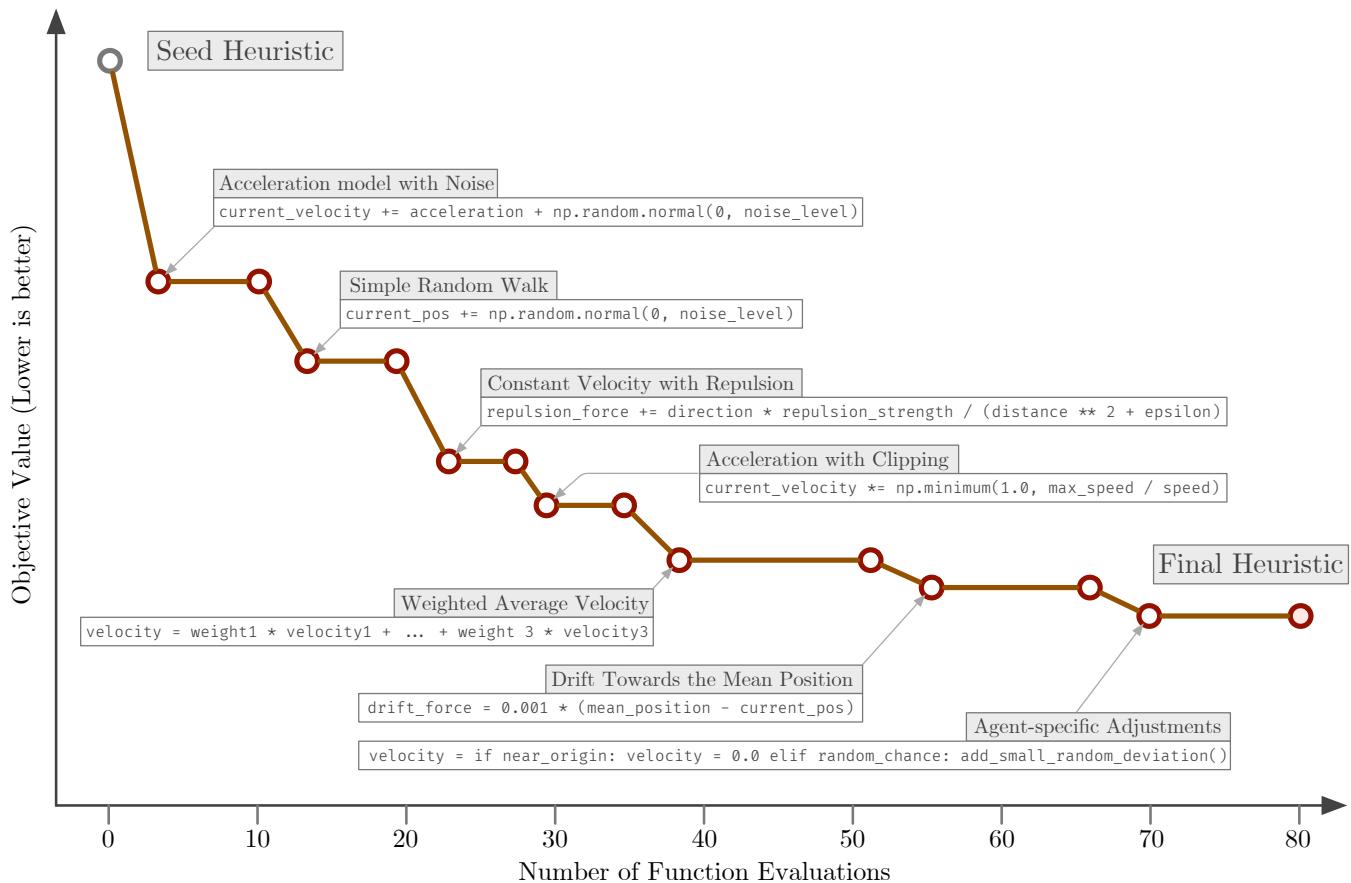


Figure 6: A qualitative illustration of the TRAJEVO evolutionary process. The optimization begins with a simple seed heuristic and iteratively discovers more complex and effective strategies by exploring different concepts like acceleration with noise, social repulsion, and weighted velocity averaging. The process converges on a final, highly-optimized heuristic that combines multiple discovered strategies, achieving a significantly lower objective value.

Experimental Details

Hyperparameters

The TRAJEVO framework employs several hyperparameters that govern the evolutionary search process and the interaction with Large Language Models. Key parameters used in our experiments are detailed in Table 6.

These include settings for population management within the evolutionary algorithm, the genetic operators, LLM-driven heuristic generation and reflection mechanisms, as well as task-specific constants for trajectory prediction evaluation. Many of

these settings were determined based on common practices in evolutionary computation, adaptations from the ReEvo framework (Ye et al. 2024), or empirically tuned for the trajectory prediction task.

Table 6: Main hyperparameters for the TRAJEVO framework.

Hyperparameter	Value
Evolutionary Algorithm	
Population size	10
Number of initial generation	8
Elite ratio for crossover	0.3
Crossover rate	1
Mutation rate	0.5
CGES Softmax temperature	1.0
Large Language Model (LLM)	
LLM model	Gemini 2.0 Flash
LLM temperature (generator & reflector)	1
Max words for short-term reflection	200 words
Max words for long-term reflection	20 words
Trajectory Prediction	
Num. prediction samples (K)	20
Observation length (T_{obs})	8 frames (3.2s)
Prediction length (T_{pred})	12 frames (4.8s)

Analysis of Exploration Ratio

In our evolutionary framework, the selection of parents for crossover is governed by an exploration-exploitation trade-off. A portion of parents is chosen uniformly at random from all successful candidates (exploration), while the remainder is selected from the top-performing elite heuristics (exploitation). To determine the optimal balance for this process, we conducted a sensitivity analysis by varying the exploration ratio from 0.0 (pure exploitation) to 1.0 (pure exploration).

The results of this analysis are presented in Figure 7. The plot shows the final Mean Squared Error (MSE) score as a function of the exploration ratio. We observed that performance generally improves as the exploration ratio increases from 0.0, reaching its peak at a ratio of 0.7. Beyond this point, further increasing the exploration led to a slight degradation in the mean performance. While a higher exploration ratio could occasionally yield a superior result in a specific run due to greater randomness, it also introduced significant performance instability, as indicated by the larger standard deviation. Therefore, an exploration ratio of 0.7 was identified as the optimal setting, offering the best balance between high performance and reliable outcomes. This value was used for all experiments conducted in this paper.

Detailed Resources

Evolution and Inference Resources We conducted a comprehensive analysis of the computational resources required by TRAJEVO and other baseline methods, covering both the one-time evolution cost and the per-instance inference cost. The results, detailed in Fig. 8 and Fig. 9, show that TRAJEVO is exceptionally efficient in both regards.

A single evolution run of TRAJEVO takes approximately 5 minutes and costs about \$0.05. In contrast, a state-of-the-art (SOTA) neural method requires a full day of training, costing around \$4.00. This efficiency is highlighted in Fig. 8. For real-time robotics applications, inference speed is critical. As shown in Fig. 9, TRAJEVO-generated heuristics require only 0.65ms on a single CPU core, while neural baselines are significantly slower, even on a GPU.

Visualizing the Impact of CGES

To complement the quantitative results presented in the main paper’s ablation study (Table 4), we provide a visual illustration of the impact of Cross-Generation Elite Sampling (CGES) on the evolutionary process. Figure 9 plots the convergence of the objective value during the evolutionary search, comparing the full TRAJEVO framework against an ablated version without CGES.

As the figure demonstrates, the inclusion of CGES allows the framework to escape local optima more effectively. The full TRAJEVO framework (represented by the red line) consistently achieves a lower (better) objective value compared to the version without CGES (blue line). This visually confirms the data in Table 4 and underscores the importance of CGES for enhancing the quality and performance of the heuristics generated during evolution. The shaded areas represent the standard deviation across multiple runs, showing the consistency of this performance improvement.

Algorithm Performance vs. Exploration Ratio

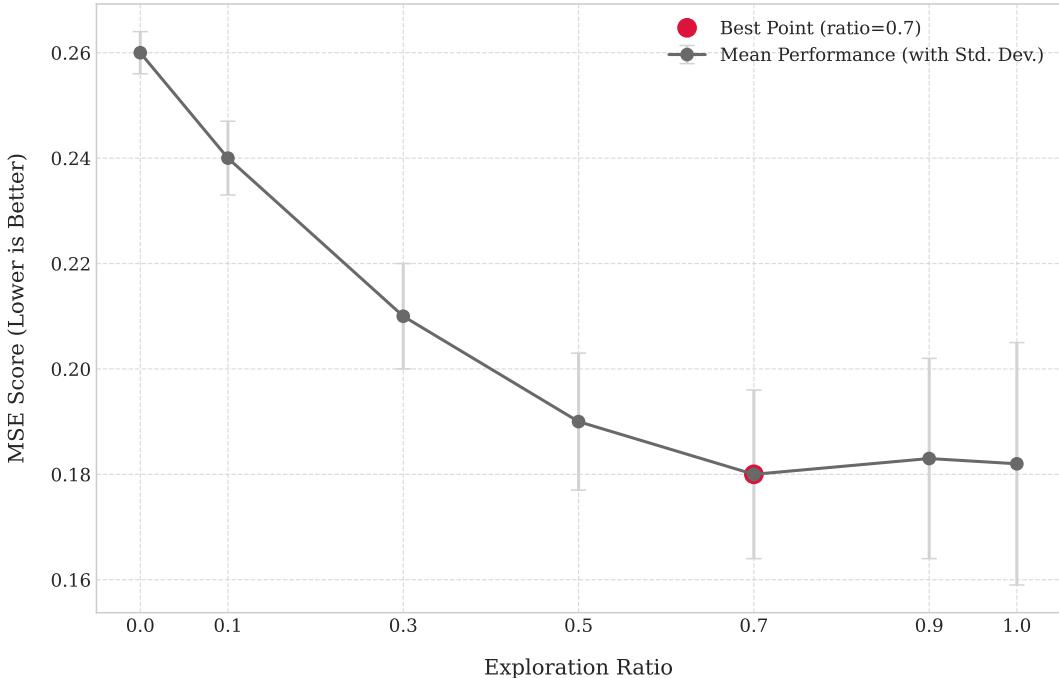


Figure 7: Performance sensitivity to the exploration ratio for crossover parent selection. The x-axis represents the proportion of parents selected uniformly at random (exploration), while the y-axis shows the resulting MSE score (lower is better). The optimal performance is achieved at an exploration ratio of 0.7, effectively balancing exploration and exploitation.

Limitations

While TRAJEVO introduces a promising paradigm for heuristic design in trajectory prediction, achieving a compelling balance of performance, efficiency, interpretability, and notably strong generalization (Table 3), we identify several limitations that also serve as important directions for future research:

In-Distribution Accuracy Although TRAJEVO significantly advances the state-of-the-art for heuristic methods and surpasses several deep learning baselines, the generated heuristics do not consistently achieve the absolute lowest error metrics on standard benchmarks compared to the most recent, highly specialized deep learning models when evaluated strictly *in-distribution*. This likely reflects the inherent complexity trade-off; heuristics evolved for interpretability and speed may have a different expressivity limit compared to large neural networks. Future work could investigate techniques to further close this gap, potentially through more advanced evolutionary operators and heuristics integration into parts of simulation frameworks while preserving the core benefits.

Input Data Complexity Our current evaluations focus on standard trajectory datasets using primarily positional history. Real-world robotic systems often have access to richer sensor data from which several features can be extracted, including agent types (pedestrians, vehicles), semantic maps (lanes, intersections), and perception outputs (detected obstacles, drivable space) – for instance, given obstacle positions, we would expect TRAJEVO to discover more likely trajectories that tend to avoid obstacles. TRAJEVO currently does not leverage this complexity. Extending the framework to incorporate and reason about such inputs would represent a significant next step. This could enable the automatic discovery of heuristics that are more deeply context-aware and reactive to complex environmental factors.

Downstream Task Performance We evaluate TRAJEVO based on standard trajectory prediction metrics (minADE/minFDE). While these metrics often correlate to downstream task performance (Phong et al. 2023), these may not always perfectly correlate with performance on downstream robotic tasks like navigation or planning. Further developing our framework to optimize heuristics directly for task-specific objectives within a closed loop (e.g., minimizing collisions or travel time in simulation) represents an interesting avenue for future works that could lead to more practically effective trajectory prediction.

Evolution Resources Comparison

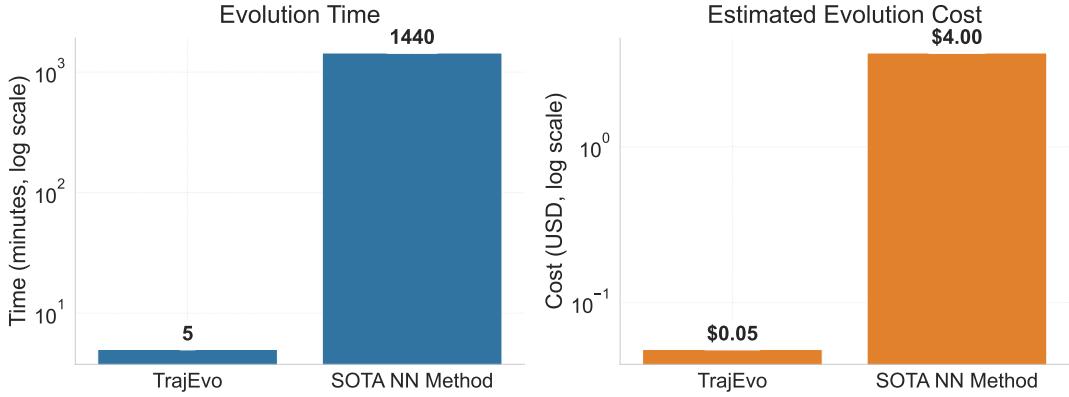


Figure 8: **Evolution Resources Comparison.** Compared to SOTA neural network methods, TRAJEVO shows a significant advantage in both evolution time and cost (e.g., 5 minutes vs. 1 day, 0.05vs. 4.00). Both metrics are displayed on a logarithmic scale.

Inference Resources Comparison

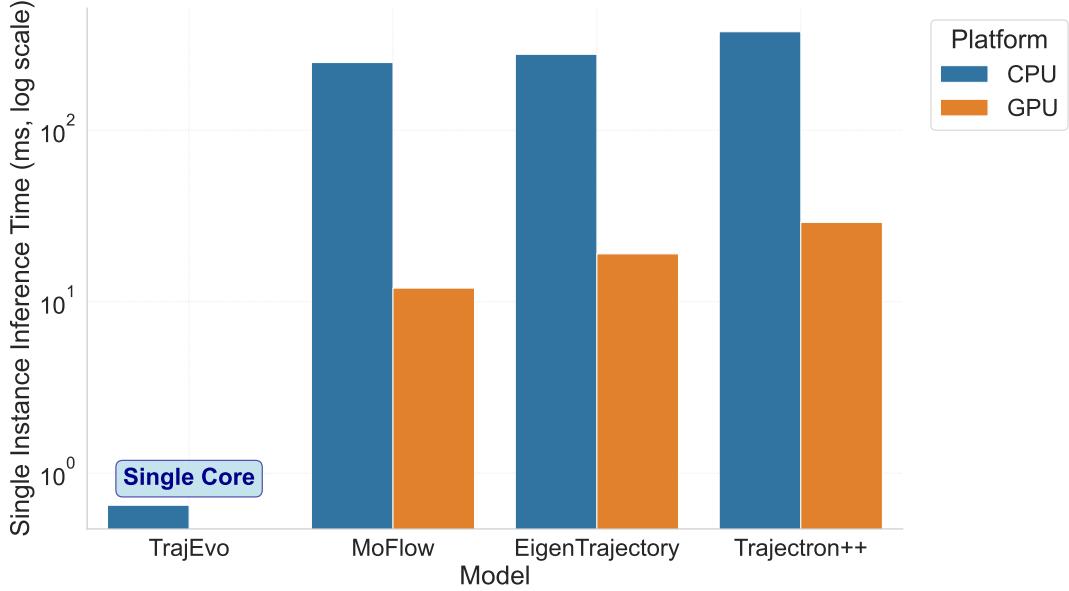


Figure 9: **Inference Resources Comparison.** TRAJEVO achieves a fast 0.65ms inference time on a single CPU core, while baseline methods require more time even on a GPU. All times are displayed on a logarithmic scale.

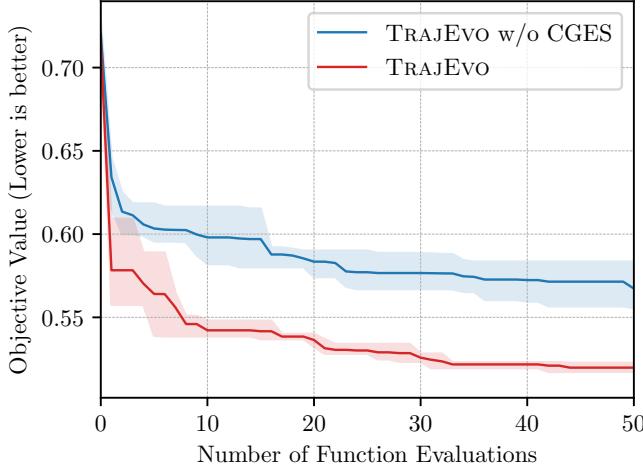


Figure 10: Visual comparison of the evolutionary process with and without CGES. The plot shows the objective value (lower is better) over the number of function evaluations, averaged over multiple runs. The TRAJEVO framework with CGES consistently converges to better solutions than the ablated version, highlighting the effectiveness of CGES in improving the search process.

Prompts

Common prompts

The prompt formats are given below for the main evolutionary framework of TRAJEVO. These are based on ReEvo (Ye et al. 2024), but with modified prompts tailored specifically for the task of trajectory prediction heuristic design and to incorporate the unique mechanisms of TRAJEVO.

```
You are an expert in the domain of prediction heuristics. Your task is to design heuristics that can effectively solve a prediction problem.  
Your response outputs Python code and nothing else. Format your code as a Python code string: ```python ... ```.
```

Prompt 1: System prompt for generator LLM.

```
You are an expert in the domain of prediction heuristics. Your task is to give hints to design better heuristics.
```

Prompt 2: System prompt for reflector LLM.

```
Write a {function_name} function for {problem_description}  
{function_description}
```

Prompt 3: Task description.

```
{task_description}  
  
{seed_function}  
  
Refer to the format of a trivial design above. Be very creative and give `{func_name}_v2`. Output code only and enclose your code with Python code block: ```python ... ```.  
  
{initial_long-term_reflection}
```

Prompt 4: User prompt for population initialization.

```
{task_description}  
  
[Worse code]
```

```

{function_signature0}
{worse_code}

[Better code]
{function_signature1}
{better_code}

[Reflection]
{short_term_reflection}

[Improved code]
Please write an improved function `(function_name)_v2`, according to the reflection. Output code only and enclose your code with Python code block: ```python ... ```.

```

Prompt 5: User prompt for crossover.

Integration of Statistics Feedback Loop The prompts for reflection and mutation are designed to leverage TRAJEVO's Statistics Feedback Loop.

Specifically, the short-term reflection prompt (Listing 6) and the elitist mutation prompt (Listing 8) explicitly require the LLM to consider "trajectory statistics" or "Code Results Analysis" when generating reflections or new heuristic code. This allows the LLM to make data-driven decisions based on the empirical performance of different heuristic strategies.

```

Below are two {func_name} functions for {problem_desc}
{func_desc}

You are provided with two code versions below, where the second version performs better than the first one.

[Worse code]
{worse_code}

[Worse code results analysis]
{stats_info_worse}

[Better code]
{better_code}

[Better code results analysis]

{stats_info_better}

Respond with some hints for designing better heuristics, based on the two code versions and the trajectory statistics. Be concise. Use a maximum of 200 words.

```

Prompt 6: User prompt for short-term reflection.

```

Below are two {function_name} functions for {problem_description}
{function_description}

You are provided with two code versions below, where the second version performs better than the first one.

[Worse code]
{worse_code}

[Better code]
{better_code}

You respond with some hints for designing better heuristics, based on the two code versions and using less than 20 words.

```

Prompt 7: User prompt for long-term reflection.

```
{user_generator}
```

```

[Prior reflection]
{reflection}

[Code]
{func_signature1}
{elitist_code}

[Code Results Analysis]
{stats_info_elitist}

[Improved code]
Please write a mutated function `{func_name}_v2`, according to the reflection. Output code only and enclose your code with Python code block: ```python ... ```.

Please generate mutation versions that are significantly different from the base code to increase exploration diversity.

```

Prompt 8: User prompt for elitist mutation.

Trajectory Prediction-specific Prompts

Domain Specialization All prompts are contextualized for the domain of trajectory prediction heuristics. For example, the system prompts are deeply contextualized through specific prompts detailing the trajectory prediction problem:

```
def predict_trajectory{version}(trajectory: np.ndarray) -> np.ndarray:
```

Prompt 9: Function Signature

```

The predict_trajectory function takes as input the current trajectory (8 frames) and generates 20 possible future trajectories for the next 12 frames. It has only one parameter: the past trajectory array.
The output is a numpy array of shape [20, num_agents, 12, 2] containing all 20 trajectories.
Note that we are interesting in obtaining at least one good trajectory, not necessarily 20.
Thus, diversifying a little bit is good.
Note that the heuristic should be generalizable to new distributions.

```

Prompt 10: Function Description

```

def predict_trajectory(trajectory):
    """Generate 20 possible future trajectories
    Args:
        - trajectory [num_agents, traj_length, 2]: here the traj_length is 8;
    Returns:
        - 20 diverse trajectories [20, num_agents, 12, 2]
    """
    all_trajectories = []
    for _ in range(20):
        current_pos = trajectory[:, -1, :]
        velocity = trajectory[:, -1, :] - trajectory[:, -2, :] # only use the last two frames
        predictions = []
        for t in range(1, 12+1): # 12 future frames
            current_pos = current_pos + velocity * 1 # dt
            predictions.append(current_pos.copy())
        pred_trajectory = np.stack(predictions, axis=1)
        all_trajectories.append(pred_trajectory)
    all_trajectories = np.stack(all_trajectories, axis=0)
    return all_trajectories

```

Prompt 11: Seed Function

```
# External Knowledge for Pedestrian Trajectory Prediction
```

```
## Task Definition
- We are using the ETH/UCY dataset for this task (human trajectory prediction)
- Input: Past 8 frames of pedestrian positions
- Output: Future 12 frames of pedestrian positions
- Variable number of pedestrians per scene
```

Prompt 12: External Knowledge

TRAJEVO Output

Generated Heuristics

```

52     velocity = velocity @ rotation_matrix
53 elif i % 6 == 2:
54     momentum = np.random.uniform(0.06, 0.14) # Vary momentum
55     velocity = momentum * velocity + (1 - momentum) * (trajectory[:, -1, :] - trajectory[:, -2, :])
56 elif i % 6 == 3: # Add jerk
57     jerk_factor = np.random.uniform(0.0025, 0.0065)
58     if history_len > 2:
59         jerk = (trajectory[:, -1, :] - 2 * trajectory[:, -2, :] + trajectory[:, -3, :])
60     else:
61         jerk = np.zeros_like(velocity)
62     velocity += jerk_factor * jerk
63 elif i % 6 == 4: # Damping
64     damping = np.random.uniform(0.006, 0.019)
65     velocity = velocity * (1 - damping)
66 else: # Adaptive Noise Scale
67     noise_scale = 0.01 + avg_speed * np.random.uniform(0.006, 0.014)
68     noise = np.random.normal(0, noise_scale, size=(num_agents, 12, 2))
69
70
71 predictions = []
72 for t in range(1, 13):
73     current_pos = current_pos + velocity + noise[:, t-1, :] / (t**0.4)
74     predictions.append(current_pos.copy())
75 pred_trajectory = np.stack(predictions, axis=1)
76
77 # Option 2: Velocity rotation with adaptive angle
78 elif i < 17: # Increased to 17.
79     velocity = trajectory[:, -1, :] - trajectory[:, -2, :]
80     avg_speed = np.mean(np.linalg.norm(velocity, axis=1))
81     angle_scale = 0.13 + avg_speed * 0.05 # adaptive angle
82
83     angle = np.random.uniform(-angle_scale, angle_scale) # adaptive range
84     rotation_matrix = np.array([[np.cos(angle), -np.sin(angle)],
85                                 [np.sin(angle), np.cos(angle)]])
86     velocity = velocity @ rotation_matrix
87
88     noise_scale = 0.007 + avg_speed * 0.004
89     noise = np.random.normal(0, noise_scale, size=(num_agents, 12, 2))
90
91 predictions = []
92 for t in range(1, 13):
93     current_pos = current_pos + velocity + noise[:, t-1, :] / (t**0.5)
94     predictions.append(current_pos.copy())
95 pred_trajectory = np.stack(predictions, axis=1)
96
97 # Option 3: Memory-based approach (repeating last velocity) + Enhanced Collision Avoidance
98 elif i < 19: # Increased to 19
99     velocity = trajectory[:, -1, :] - trajectory[:, -2, :]
100    # Enhanced smoothing with more velocity history
101    if history_len > 3:
102        velocity = 0.55 * velocity + 0.3 * (trajectory[:, -2, :] - trajectory[:, -3, :]) + 0.15 * (
103            trajectory[:, -3, :] - trajectory[:, -4, :])
104    elif history_len > 2:
105        velocity = 0.65 * velocity + 0.35 * (trajectory[:, -2, :] - trajectory[:, -3, :])
106    else:
107        velocity = velocity # do nothing
108
109    avg_speed = np.mean(np.linalg.norm(velocity, axis=1))
110
111    # Adaptive Laplacian noise
112    noise_scale = 0.005 + avg_speed * 0.0015
113    noise = np.random.laplace(0, noise_scale, size=(num_agents, 2))
114    velocity = velocity + noise
115
116    # Enhanced collision avoidance

```

```

116     repulsion_strength = 0.0011 # Adjusted repulsion strength
117     predictions = []
118     temp_pos = current_pos.copy()
119
120     # Store predicted positions for efficient collision calculation at each timestep
121     future_positions = [temp_pos.copy()] # Start with current position
122     for t in range(1, 13):
123         net_repulsions = np.zeros_like(temp_pos)
124         for agent_idx in range(num_agents):
125             for other_idx in range(num_agents):
126                 if agent_idx != other_idx:
127                     direction = temp_pos[agent_idx] - temp_pos[other_idx]
128                     distance = np.linalg.norm(direction)
129                     if distance < 1.05: # Adjusted interaction threshold
130                         repulsion = (direction / (distance + 1e-6)) * repulsion_strength * np.exp(-distance)
131             # distance-based decay
132             net_repulsions[agent_idx] += repulsion
133
134             velocity = 0.9 * velocity + 0.1 * net_repulsions # Damping the change in velocity
135             temp_pos = temp_pos + velocity
136             future_positions.append(temp_pos.copy()) # Store for future repulsion calculations
137             predictions.append(temp_pos.copy())
138
139             pred_trajectory = np.stack(predictions, axis=1)
140
141     # Option 4: Linear prediction with adaptive damping and larger noise.
142     else:
143         velocity = trajectory[:, -1, :] - trajectory[:, -2, :]
144         damping = np.random.uniform(0.017, 0.038) # damping factor
145
146         noise_scale = 0.028
147         noise = np.random.normal(0, noise_scale, size=(num_agents, 12, 2))
148
149         predictions = []
150         for t in range(1, 13):
151             velocity = velocity * (1-damping) + noise[:, t-1, :] / (t**0.4) # damping
152             current_pos = current_pos + velocity
153             predictions.append(current_pos.copy())
154             pred_trajectory = np.stack(predictions, axis=1)
155
156         all_trajectories.append(pred_trajectory)
157
158     all_trajectories = np.stack(all_trajectories, axis=0)
159     return all_trajectories

```

Heuristic 13: The best TRAJEVO-generated heuristic for Zara 1.

Reflections

Based on comparative analysis, prioritize these heuristics:

1. **Hierarchical Stochasticity:** Sample trajectory-level parameters (speed scale, movement pattern) *once* per trajectory. Then, apply agent-specific stochastic variations within those constraints. Introduce `global_randomness` sampled *once* per trajectory to couple different parameters.
2. **Adaptive Movement Primitives:** Condition movement model probabilities (stop, turn, straight, lane change, obstacle avoidance) on agent state (speed, acceleration, past turning behavior, context). Consider longer history windows.
3. **Refine Noise & Parameters:** Finetune noise scales and apply dampening. Experiment with learnable parameters and wider ranges. Directly manipulate velocity and acceleration stochastically for smoother transitions.
4. **Contextual Interactions:** Enhance social force models, considering intentions, agent types, and environment.
5. **Guaranteed Diversity:** Ensure movement probabilities sum to 1.
6. **Post Processing:** Apply smoothing and collision avoidance.

```
7. **Intentions:** Incorporate high level intentions such as "going to an area."
```

Output 14: Long-term reasoning output

Listing 14 shows an example of long-term reasoning output for the model, based on the comparative analysis. TRAJEVO discovers several interesting heuristics for trajectory forecasting, such as applying diverse noise factors, social force models, diversity, and modeling intentions to model possible future trajectories.

Listing 15 shows some more outputs of TRAJEVO from various runs, which discovers some interesting helper functions that model interactions such as stochastic, social force, and diversity.

```
42 #####
43 # Model with Noise
44 #####
45
46 def acceleration_model_with_noise(traj, noise_level_base=0.05, prediction_steps=12):
47     velocity = traj[:, -1, :] - traj[:, -2, :]
48     acceleration = velocity - (traj[:, -2, :] - traj[:, -3, :])
49     current_pos = traj[:, -1, :].copy()
50     current_velocity = velocity.copy()
51     predictions = []
52     for i in range(prediction_steps):
53         noise_level = noise_level_base * (i + 1)
54         current_velocity = current_velocity + acceleration + np.random.normal(0, noise_level, size=current_velocity.shape)
55         current_pos = current_pos + current_velocity
56         predictions.append(current_pos.copy())
57     return np.stack(predictions, axis=1)
58
59
60 #####
61 # Social Force
62 #####
63
64 def constant_velocity_with_repulsion(traj, get_nearby_agents, repulsion_strength=0.05, num_steps=12):
65     velocity = traj[:, -1, :] - traj[:, -2, :]
66     current_pos = traj[:, -1, :].copy()
67     repulsion_force = np.zeros_like(current_pos)
68     num_agents = traj.shape[0]
69
70     for _ in range(num_steps):
71         for agent_index in range(num_agents):
72             nearby_agents = get_nearby_agents(agent_index, current_pos)
73             for neighbor_index in nearby_agents:
74                 direction = current_pos[agent_index] - current_pos[neighbor_index]
75                 distance = np.linalg.norm(direction)
76                 if distance > 0:
77                     repulsion_force[agent_index] += (direction / (distance**2 + 0.001)) * repulsion_strength
78     return repulsion_force
79
80
81 #####
82 # Diversity
83 #####
84
85 def simple_random_walk(traj, noise_level_base=0.2, prediction_steps=12):
86     current_pos = traj[:, -1, :].copy()
87     predictions = []
88     for _ in range(prediction_steps):
89         noise_level = noise_level_base * (_ + 1)
90         current_pos = current_pos + np.random.normal(0, noise_level, size=current_pos.shape)
91         predictions.append(current_pos.copy())
92     return np.stack(predictions, axis=1)
```

Output 15: Selected TRAJEVO Interactions