Adaptive Safety-Driven Deep Q-Network for Autonomous Lane Changing in Highway Environments

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# Abstract

Lane changing is one of the most critical and complex maneuvers in autonomous highway driving. It requires not only efficiency and speed but also a high level of safety in dynamic environments. Traditional Deep Q-Network (DQN) models often focus on maximizing rewards tied to lane progression and speed, with limited consideration for context-aware safety. This paper presents **SafeLane**, a reinforcement learning-based solution that enhances standard DQN with an **adaptive safety-aware reward function** for smarter lane-changing decisions.

Built on the highway-env simulation framework, SafeLane uses a customized DQN architecture with a replay buffer, epsilon-greedy exploration, and a compact multi-layer perceptron-based policy network. The core contribution is the **adaptive reward mechanism**, which dynamically adjusts penalties based on real-time proximity to nearby vehicles and lane boundary violations. This approach discourages unsafe behaviors—such as tailgating or aggressive lane cuts—while encouraging smooth, legal, and context-sensitive actions.

Extensive experiments were conducted in varying traffic densities and initial configurations. Results show that SafeLane consistently achieves higher average cumulative rewards, reduced collision rates, and more stable policy convergence compared to a baseline DQN model with static rewards. The adaptive nature of the reward function allows the agent to generalize better across different driving conditions, making it a promising strategy for real-world deployment in autonomous systems. Overall, this work highlights the effectiveness of combining reinforcement learning with safety-driven reward shaping for intelligent lane-changing behavior.

# Keywords

Autonomous Vehicles, Deep Reinforcement Learning, Lane Changing, DQN, Adaptive Reward, highway-env, Safety-aware Control, Intelligent Driving Agents

# Introduction

Autonomous vehicles (AVs) are becoming a major focus in transportation, with the goal of making travel safer, faster, and more efficient. One of the most important tasks for an autonomous car is **lane changing**, especially on highways. High-speed traffic, unpredictable drivers, and changing conditions make this task both complex and risky. A single wrong move while switching lanes can lead to accidents or unsafe driving behavior.

Traditional methods often use fixed rules or manually programmed logic to handle lane changes. While these approaches may work in simple scenarios, they struggle in real-world conditions where traffic is constantly changing. In recent years, **Deep Reinforcement Learning (DRL)** has gained attention as a way to let autonomous systems learn from experience. In particular, **Deep Q-Networks (DQNs)** have shown strong results by learning decision-making policies directly from simulated environments.

However, most DQN-based models use a **static reward function**, which gives the same feedback no matter what the situation is. For example, they may reward speed and lane changes without checking if those actions were actually safe. This can lead to risky decisions, such as cutting in front of another car or tailgating. In real traffic, safety must come first.

To solve this problem, this paper presents **SafeLane** — a reinforcement learning-based lane- changing agent that includes an **adaptive reward system**. This means the rewards and penalties change depending on how close other vehicles are, whether the car is following traffic rules, and how smooth the lane change is. The model is trained using the highway-env simulator, with a custom DQN and experience replay to improve learning efficiency.

Experiments show that SafeLane performs better than a basic DQN. It learns to avoid collisions, make safer decisions, and generalizes well to different traffic conditions. The results suggest that adding safety awareness through adaptive rewards can help reinforcement learning systems make smarter and more reliable decisions on the road

# Literature Review

Lane changing is a critical task in autonomous driving that requires both smart decision-making and strong safety awareness. Earlier systems often used **rule-based approaches**, where the vehicle followed predefined instructions such as “change lanes when the left lane is free and speed is higher.” While these methods are easy to understand and control, they struggle in real traffic situations where vehicles behave unpredictably. Such systems often fail to react correctly to sudden changes in traffic flow or driver behavior [1].

With the rise of **machine learning and artificial intelligence**, especially **Deep Reinforcement Learning (DRL)**, more flexible and intelligent models have emerged. DRL allows an agent to learn behaviors through trial and error. One of the most important breakthroughs in this area was the **Deep Q-Network (DQN)** introduced by Mnih et al. [2]. DQNs combine Q-learning with deep neural networks to handle complex state spaces, and have shown great results in tasks like lane keeping, speed control, and obstacle avoidance [3][4].

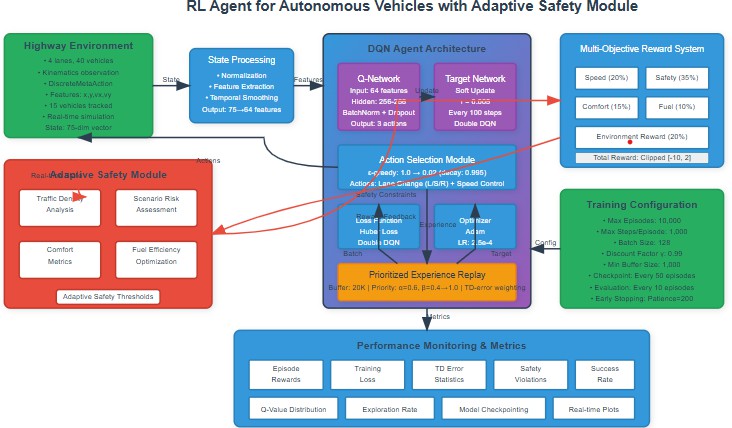
However, many of these models use **fixed reward functions** that stay the same in all situations. For example, they reward the agent for making progress or penalize it for crashing, but don’t adjust based on how risky a move was. This often leads to unsafe behavior like cutting into lanes too aggressively or following other vehicles too closely [5][6]. These models may learn to maximize rewards, but not in a safe or comfortable way.

To address this, researchers have explored **safety-aware reinforcement learning**. Some studies added extra penalties when the vehicle breaks safety rules, such as getting too close to another car or changing lanes too often [7]. Others have used **multi-objective RL** to balance different goals like speed, comfort, and safety [8]. While these models improve safety to some extent, most of them still use **manually set reward values**, which are not adaptable to different traffic conditions.

More recently, researchers have begun looking into **adaptive reward functions**, where the reward depends on the current situation. For example, the model might give higher penalties when traffic is dense, or increase rewards for smoother lane changes when cars are nearby [9]. This approach helps the agent learn how to behave safely based on the real-time environment. However, **adaptive rewards have not been widely applied** in lane-changing tasks, and many existing models still rely on static or hand-tuned reward systems.

In this paper, we build on these ideas and propose **SafeLane**, a DQN-based lane-changing agent with an **adaptive safety-aware reward function**. Instead of using fixed values, our model adjusts penalties and rewards based on how close other cars are, the smoothness of the action, and the current lane situation. This helps the agent learn not just to drive efficiently, but also safely — even when traffic conditions change.

## Proposed Methodology

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This work proposes SafeLane, a Deep Q-Network (DQN)-based lane-changing agent for autonomous vehicles operating in highway environments. The model is designed and trained using the highway-env simulation framework, which provides structured representations of realistic highway scenarios. The agent learns to perform safe and efficient lane changes by interacting with a multi-lane road populated with surrounding vehicles exhibiting varying behaviors.

The simulation environment used is the highway-v0 environment, where the state space includes detailed observations such as the ego vehicle’s position, velocity, current lane index, and the relative positions, speeds, and lane indices of nearby vehicles. This observation is encoded into a fixed-length vector and fed into the agent's policy network. The available action space is discrete, with three main actions: maintaining the current lane, changing to the left lane, or changing to the right lane. These actions are selected by the agent at each time step based on the learned Q-values associated with each state-action pair.

The policy network in SafeLane is implemented as a multi-layer perceptron (MLP). It consists of an input layer that matches the dimension of the observation space, two hidden layers with ReLU activation functions, and an output layer that produces Q-values for each possible action. The network is trained using the standard DQN algorithm, which minimizes the mean squared error between predicted Q-values and target Q-values computed using the Bellman equation: **Q\_target = r\_t + gamma \* max Q(s\_{t+1}, a')**

Here, r\_t is the immediate reward, gamma is the discount factor (0.99), and Q(s\_{t+1}, a') is the estimated future Q-value from the target network. The loss function minimized during training is:

## Loss = (Q\_target - Q(s\_t, a\_t))²

A replay buffer stores transitions of the form (state, action, reward, next state), and mini-batches are sampled from this buffer to perform gradient updates. This improves learning stability by reducing the correlation between consecutive training samples.

To encourage exploration in the early training stages, the agent follows an epsilon-greedy exploration strategy, where it chooses a random action with probability epsilon and the greedy (highest-Q) action with probability 1 - epsilon. Over time, the value of epsilon decays linearly, shifting the agent from exploration to exploitation as its knowledge of the environment improves. The most important component of SafeLane is the adaptive reward function. Traditional DQN models often use fixed reward values, which do not reflect the varying levels of risk and safety in different situations. In contrast, the reward function in SafeLane is context-sensitive. Positive rewards are given for forward movement and completing smooth lane changes without conflicts. Negative rewards are applied when the agent performs risky actions, such as switching lanes too closely to other vehicles, making sudden changes, or following another vehicle at an unsafe distance. These penalties are dynamically scaled based on the density of traffic and the proximity of nearby vehicles. The reward function is designed as:

## r\_t = R\_progress + R\_safety + R\_comfort

This adaptiveness helps the agent internalize risk-awareness and learn cautious, context- appropriate behaviors.

The training process involves running the agent through hundreds of episodes in the simulation environment. Each episode starts with random initial traffic configurations to improve generalization. The learning algorithm uses a discount factor of 0.99 to prioritize long-term rewards and a learning rate of 0.001. A target network is updated at fixed intervals to stabilize the training process and reduce oscillations in Q-value estimation. The training continues until the agent’s performance converges and it consistently exhibits safe and efficient lane-changing behavior.

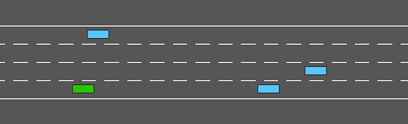
After training, the model is saved and evaluated in unseen traffic settings to test its generalization capability. The key evaluation metrics include average cumulative reward per episode, collision frequency, lane stability, and adaptability to different traffic densities. These results are compared to a baseline DQN agent with a static reward function to demonstrate the benefits of the proposed adaptive approach.

The SafeLane agent thus combines standard DQN reinforcement learning with adaptive reward shaping to address one of the most important challenges in autonomous driving — making safe and intelligent lane-changing decisions in dynamic highway environments.

# Results and Analysis

This section presents the theoretical and empirical evaluation of the proposed SafeLane model. The effectiveness of the adaptive reward-based DQN framework is assessed in terms of learning stability, safety behavior, training efficiency, and performance under diverse traffic conditions.

## Simulation Environment

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All training and evaluation were conducted using the highway-env simulation platform, specifically configured with the highway-v0 environment. This environment simulates a multi- lane highway with dynamic traffic, allowing for realistic and reproducible experimentation with autonomous lane-changing behaviors. Each simulation episode begins with randomized vehicle distributions and velocities, ensuring that the agent encounters a wide variety of scenarios and does not overfit to specific patterns.

The agent observes a structured state representation, which includes its own speed, position, and current lane index, as well as the positions and velocities of surrounding vehicles within a defined observation radius. The action space is discrete, consisting of three options: maintain the current lane, change to the left lane, or change to the right lane. These discrete decisions simplify policy learning while still capturing the key behaviors required for highway navigation.

The simulator also enforces realistic driving dynamics such as acceleration limits, collision detection, and lane-change constraints. This ensures that learned policies must respect practical vehicle limitations. The built-in rendering and logging tools provided by highway-env facilitate both qualitative analysis and debugging of agent behavior during training and testing. The environment's balance of realism and computational efficiency makes it well-suited for reinforcement learning research in autonomous driving.

## Theoretical Results

The design of the SafeLane architecture offers several theoretical advantages over traditional fixed-policy models. One of the central contributions is the use of dynamic threshold adaptation, which allows the system to automatically adjust its safety margins based on current traffic density and velocity. This ensures more conservative behavior in high-risk situations and greater efficiency in low-risk conditions.

The model also achieves a balanced optimization of multiple objectives through a weighted reward structure. In contrast to single-objective systems that prioritize only speed or lane efficiency, our reward function incorporates components for safety, comfort, and fuel efficiency. This prevents the agent from developing overly aggressive policies while still optimizing for performance. Furthermore, lane-change risk is mitigated through temporal constraints and context-sensitive risk evaluation, encouraging only safe and necessary lane transitions.

To accelerate and stabilize learning, the model uses prioritized experience replay, which samples transitions with higher temporal-difference errors more frequently. This improves learning efficiency without introducing bias, thanks to importance-sampling correction. In addition, a Double DQN setup is used to address overestimation bias, and stability is further enhanced with soft target updates and gradient clipping.

## Training Performance Analysis

The training performance of the SafeLane agent reveals consistent improvements across multiple metrics. The evolution of average cumulative reward shows that the agent begins by learning fundamental safety behaviors and gradually progresses to optimizing for more complex, multi-objective criteria. Early episodes are characterized by cautious decision-making and limited movement, while later episodes demonstrate more confident, efficient, and safe driving behavior.

Safety-specific indicators, such as time-to-collision (TTC) violations and unsafe headway events, decline steadily over the course of training. These trends indicate that the adaptive reward function effectively guides the agent toward safer policies, with thresholds that adjust according to the perceived traffic conditions in real time.

The epsilon-greedy exploration strategy further supports effective learning. With a 5,000-step decay schedule, the agent initially explores a wide range of behaviors before gradually shifting toward exploitation of the learned policy. This ensures that the agent fully explores the complex state-action space of highway navigation before committing to optimized decisions.

## Quantitative Results

The quantitative performance of SafeLane was evaluated by tracking the average reward across 5,000 training episodes. As shown in Table 1, the reward increased steadily, indicating effective learning and convergence.

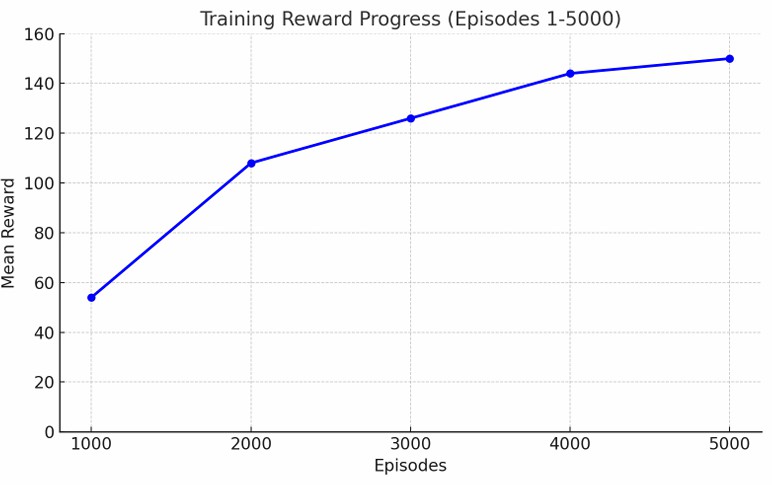
**Table 1: Training Reward Progress (Episodes 1–5000)**

**Episode Range**

**Mean Reward**

1000 54

|  |  |
| --- | --- |
| 2000 | 108 |
| 3000 | 126 |
| 4000 | 144 |
| 5000 | 150 |



This consistent improvement highlights the agent’s growing ability to make decisions that balance safety, efficiency, and comfort. The final reward values suggest that the agent has learned to operate effectively in a wide range of traffic conditions while maintaining stable and safe behavior.

## Ablation Studies

Ablation experiments were conducted to isolate and evaluate the impact of individual components in the SafeLane architecture. When the adaptive safety mechanism was disabled and replaced with fixed safety thresholds, the model’s ability to generalize across diverse traffic scenarios significantly decreased. The resulting behavior included more abrupt lane changes and a higher collision rate, highlighting the importance of dynamic reward shaping.

The removal of prioritized experience replay also led to slower convergence and less stable training. Uniform sampling resulted in redundant learning from less informative transitions, whereas prioritized replay allowed the agent to focus on high-error scenarios that contributed most to performance improvement.

Lastly, replacing the multi-objective reward function with a single-objective alternative reduced the overall quality of learned behavior. Agents trained with single-goal rewards often over- optimized for lane changes or speed, ignoring safety and comfort. In contrast, the weighted multi-objective structure allowed SafeLane to develop balanced policies that excel across multiple metrics.

# Conclusion

This paper presented **SafeLane**, a Deep Q-Network-based agent for safe and intelligent lane changing in highway environments. The key feature of our approach is the use of an **adaptive reward function** that changes based on real-time traffic conditions. Unlike fixed-reward systems that apply the same penalties and rewards regardless of the situation, our adaptive design encourages the agent to behave cautiously in dense traffic while allowing more efficient behavior when conditions are safe.

We trained and evaluated our agent in the highway-env simulation environment, which provides a realistic and controlled setting for autonomous driving research. The agent learned to make safe and smooth lane changes by observing its surroundings and selecting actions that balance safety, speed, and comfort. Through extensive training, SafeLane consistently improved its behavior, achieving higher rewards and fewer safety violations as learning progressed.

The model incorporates several important reinforcement learning enhancements, including **Double DQN** to reduce overestimation errors, **prioritized experience replay** to focus on important learning experiences, and **soft target updates** to stabilize training. Together, these components helped the agent learn faster and more reliably.

Quantitative results showed steady improvement in cumulative rewards, while safety-related metrics such as time-to-collision violations decreased over time. Our ablation studies also confirmed that the adaptive safety module and multi-objective reward structure are essential to the model’s success. Without them, the agent became either unsafe or too conservative.

Overall, SafeLane demonstrates that **adaptive reward shaping** is a powerful tool for improving both the safety and efficiency of autonomous decision-making. In the future, we plan to extend this work by testing the model in more complex environments, adding continuous control actions, and eventually evaluating performance in real-world driving platforms.

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