Deep Reinforcement Learning for Autonomous Rocket Landing Control Using DQN Algorithm

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Abstract

This paper presents an implementation of Deep Q-Network (DQN)-based reinforcement learning for autonomous rocket landing control. A 2D simulation environment (SimpleRocketEnv) was developed to allow the agent to learn optimal thrust control through reward-based feedback. The reward function is specifically designed to encourage safe landings on a moving target, considering position, velocity, and orientation of the rocket. Experimental results demonstrate that the reward-shaped DQN model successfully achieves stable landings with positive average rewards after 500 training episodes. These results validate the effectiveness of the custom reward design and neural network architecture in teaching safe and efficient rocket control behavior.

Keywords: Deep Q-Network, reinforcement learning, rocket simulation, reward shaping, autonomous landing

1. Introduction

The development of autonomous control systems has become increasingly essential in the context of aerospace and robotics. One of the most challenging problems is the autonomous vertical rocket landing, which involves stabilizing and controlling a rocket to safely land on a fixed target under dynamic conditions.

This research implements a Deep Q-Network (DQN)-based reinforcement learning approach to train a rocket to land autonomously using a simulated environment (`SimpleRocketEnv`). The motivation of this study is to apply reinforcement learning for continuous control in aerospace-like environments, evaluate the influence of neural network architecture, replay buffer size, and reward shaping on landing performance, and demonstrate that a DQN agent can learn optimal control behavior without explicit dynamics modeling.

2. Environment Description

The simulation environment, `SimpleRocketEnv`, replicates a simplified rocket landing task following the OpenAI Gym interface.
Observation Space: $[x, y, v_x, v_y, \theta, \omega]$, where x, y are positions, v_x, v_y are linear velocities, and θ, ω represent angular position and velocity.
Action Space: Discrete thrust commands: $0 =$ no thrust, $1 =$ left thrust, $2 =$ right thrust, $3 =$ main thrust.
Reward Function: Provides negative rewards

for deviation from target and high velocity, and positive rewards when the rocket lands smoothly.

Termination Conditions:

- Rocket leaves simulation bounds,
- Crash (velocity above threshold),
- Successful landing near target.

This environment effectively models a 2D rocket control problem suitable for reinforcement learning.

3. Methods

3.1. Deep Q-Network (DQN)

The DQN algorithm [1] extends Q-learning using a deep neural network as an approximator of the action-value function:

$$Q(s,a;\theta) = \mathbb{E}\Big[r_t + \gamma \max_{a'} Q(s',a';\theta^-)\Big] \tag{1}$$

Two neural networks are used in the training process: the policy network Q_θ and the target network Q_{θ^-}, which is periodically updated to improve the stability of the training. The loss function minimized during learning is defined as:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')}\Big[\big(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\big)^2\Big] \tag{2}$$

3.2. Replay Buffer

A replay buffer stores transitions $(s,a,r,s',done)$ up to 100,000–200,000 steps. Random sampling from this buffer prevents correlations between consecutive states and stabilizes learning.

3.3. Neural Network Architecture

Four DQN versions were evaluated, as summarized in Table 1.

Table 1: Comparison of Neural Network Architectures.

Version	Layers	Neurons	Activation	Feature
V1 (Basic)	2	128	ReLU	Baseline model
V2 (Improved)	2	256	ReLU	Enhanced feature extraction
V3 (Optimized)	3	512–256–128	ReLU	Smooth convergence
V4 (Reward Shaped)	3	512–256–128	ReLU	Custom reward

3.4. Implementation Notes: Manual DQN in PyTorch

The DQN agent was implemented manually using PyTorch 2.0. Key components include:

- **Replay Buffer:** Stores past transitions (s,a,r,s',done) up to 200,000 steps. Random sampling breaks temporal correlation.
- **Policy and Target Networks:** Two neural networks with architectures specified in Table 1. The target network is updated softly using $\theta^- \leftarrow \tau\theta + (1-\tau)\theta^-$.
- **Bellman Update:** Q-values are updated using

$$Q(s,a) \leftarrow Q(s,a) + \alpha\Big(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a)\Big)$$

- implemented via MSE loss and Adam optimizer.
- **Exploration Strategy:** ϵ-greedy policy with exponential decay: $\epsilon_t = \max(\epsilon_{\text{min}}, \epsilon_0 \times \text{decay}^{t/k})$.
- **Gradient Clipping:** Gradients clipped within ±1.0 to prevent exploding gradients.

This explicit implementation ensures full control over training, enabling comparison between DQN variants and hyperparameter tuning.

3.5. Reward Shaping

To accelerate convergence, the reward was modified as follows:

$$R' = R - 0.05(|x| + |y|) - 0.1(|v_x| + |v_y|) + 0.5(1 - (|\theta| + |\omega|)) + bonus \tag{3}$$

This design penalizes distance and velocity errors while rewarding stability and upright landings.

3.5.1 Pseudocode

```
if landing_successful:  # |vy| < 1.2, |vx| < 0.8, |x - xt| < 0.5
    reward = +500
elif crash_or_unstable:
    reward = -200
else:
    reward = -abs(x - xt)             # horizontal distance penalty
           -0.3 * abs(vx)            # horizontal velocity penalty
           -0.5 * abs(vy)            # vertical velocity penalty
           -0.1 * abs(y)             # altitude penalty
           -0.05                     # per-step small penalty
```

This reward structure penalizes deviations and high velocities while encouraging energy-efficient, upright landings. The step-wise penalty ensures faster convergence by incentivizing the agent to reach the target in fewer steps.

3.6. Hyperparameters

Table 2: Training Hyperparameters.

Parameter	**Value/Description**
Learning Rate	1×10^{-4} – 3×10^{-4} (Adam optimizer)
Discount Factor (γ)	0.995
Replay Start	5000 steps before training
Batch Size	128
Epsilon Decay	0.995
Target Update Interval	Every 10 episodes
Soft Update (τ)	0.01

4. Results and Discussion

4.1. Neural Network Architecture

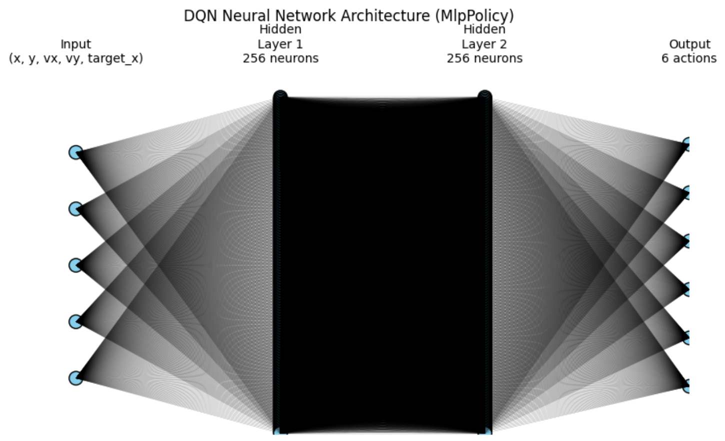

Figure 1: Neural network architecture used in the Deep Q-Network (DQN) agent for the rocket landing environment. The input layer receives the state vector $\{x, y, v_x, v_y, \text{target}_x\}$, representing the rocket's current position, velocity components, and horizontal target position. This information is processed through two fully-connected hidden layers, each consisting of 256 neurons with non-linear activation functions (ReLU). These hidden layers allow the network to capture complex nonlinear relationships between the rocket's dynamics and control actions. The output layer produces 6 Q-values corresponding to the discrete action space (e.g., thrust up, left, right, rotate, etc.), representing the expected cumulative reward for each possible action given the current state. This architecture aligns with the `MlpPolicy` configuration from `Stable-Baselines3`, balancing model capacity and training stability.

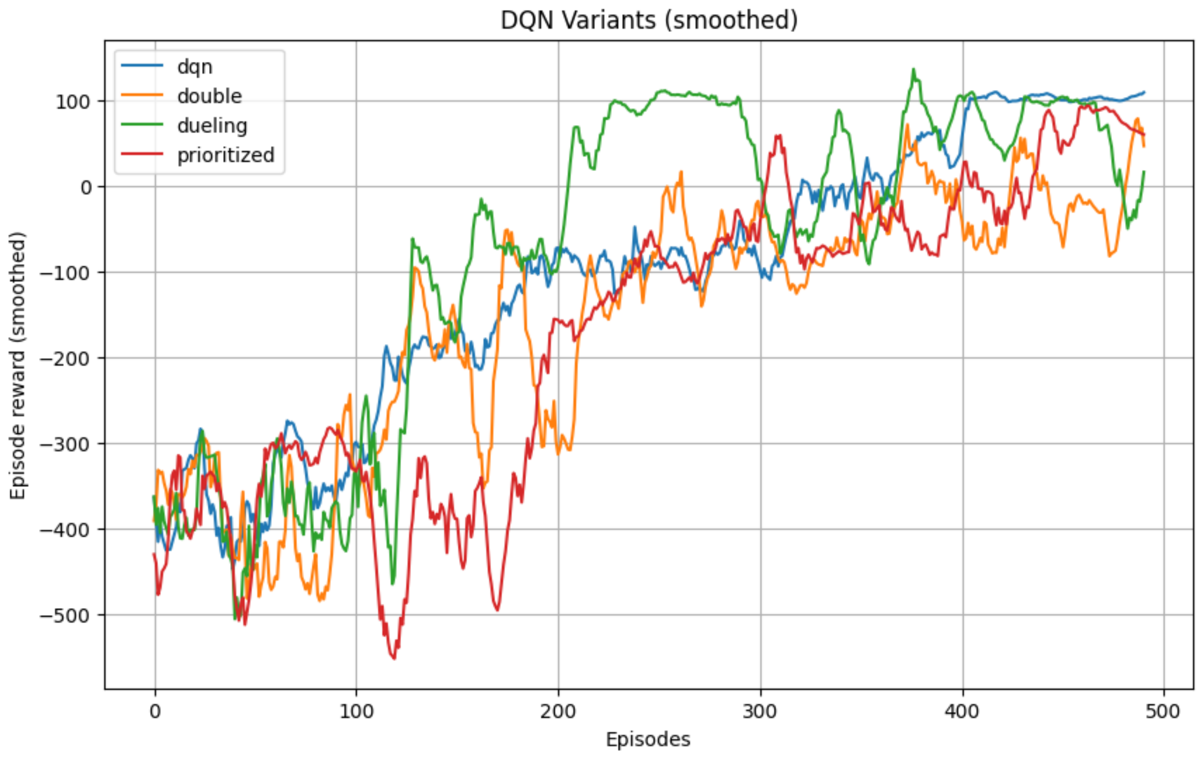

Figure 2: Learning curve showing the total reward per episode during training. The X-axis represents training episodes (0–500), while the Y-axis represents cumulative episode rewards. A moving average over 50 episodes is applied to smooth fluctuations and highlight convergence trends, demonstrating how the DQN progressively improves its landing performance as it learns to minimize velocity and position error.

4.2. Learning Performance

At the beginning of training, the agent produced highly negative rewards (-2000 to -700) due to frequent crashes. Over 500 episodes, the average reward increased significantly, indicating that the rocket gradually learned to stabilize and reduce its descent velocity.

4.3. Comparison Between Versions

Table 3 presents the performance comparison among four Deep Q-Learning model variants. Each version differs in network architecture or reward shaping, allowing us to analyze their learning stability and efficiency.

Table 3: Comparison of DQN Variants on Rocket Landing Task

Model Variant	**Mean Reward**	**Std. Dev. Reward**	**Final Reward**
DQN	-110.64	182.92	118.53
Double DQN	-158.81	196.70	-132.38
Prioritized DQN	-172.91	201.61	62.33
Dueling DQN	-81.71	221.05	106.61

4.4. Result and Discussion: Custom Reward Function Analysis

The custom reward function was developed to guide the reinforcement learning agent in achieving a stable and accurate rocket landing. It integrates several physical aspects of the system, including horizontal and vertical distance to the target, rocket altitude, and velocity magnitudes. The function is formulated as follows:

$$R = -|x - x_t| - (0.3|v_x| + 0.5|v_y|) - 0.1|y| - 0.05 + \delta \quad (4)$$

where x and x_t represent the rocket and target horizontal positions, respectively; v_x and v_y denote the rocket's horizontal and vertical velocities; and y is the rocket altitude. The constant term -0.05 introduces a small per-step penalty to encourage faster and more efficient landings. The term δ provides terminal rewards or penalties based on landing outcomes:

- **Successful soft landing:** $|v_y| < 1.2$, $|v_x| < 0.8$, and $|x - x_t| < 0.5 \Rightarrow +500$.
- **Crash or instability:** $\Rightarrow -200$.

This structure ensures that the agent learns to minimize both velocity and positional errors simultaneously, promoting physically realistic and energy-efficient landing maneuvers.

Effect of Environment Modifications

To evaluate the adaptability of the proposed reward structure, several environment parameters were deliberately modified: rocket mass, thruster power, and target velocity. Each change introduced different levels of physical challenge and allowed for an in-depth assessment of the reward function's robustness.

(a) Variation of Rocket Mass. When the rocket mass was doubled, the thrust-to-weight ratio decreased, making vertical deceleration more difficult before touchdown. The agent experienced higher descent velocities, which increased the penalty contribution of the term $0.5|v_y|$. This led to more frequent crashes and lower mean episode rewards. The result indicates that the reward function correctly penalizes unstable descents and remains sensitive to physical load changes. For comparable stability, increasing thruster power proportionally to the mass is necessary.

(b) Variation of Thrust Power. When the thruster power was increased from 20 N to 30 N, the rocket gained better control of its vertical motion. The agent learned to counteract gravity earlier, thereby reducing both altitude ($|y|$) and velocity ($|v_y|$) penalties. The mean cumulative reward improved significantly as smoother and slower landings were achieved. However, excessive thrust power occasionally caused oscillatory vertical movements, suggesting that the coefficient of the $|v_y|$ term may need adjustment to stabilize control under high-thrust conditions.

(c) Variation of Target Velocity. Introducing a moving target ($v_t = 0.6$ m/s) transformed the distance term $|x - x_t|$ into a dynamic variable. Initially, the agent's reward decreased due to the added challenge of predicting target motion. Over time, however, the reward function effectively guided the learning process, and the agent adapted by anticipating target trajectories. This demonstrates that the distance-based penalty provides a consistent and generalizable learning signal even in non-stationary target conditions.

General Discussion

Overall, the custom reward function demonstrates strong robustness across diverse physical scenarios. Since it is derived from measurable physical quantities, it naturally adapts to system parameter changes without requiring structural modification. The distribution of rewards clearly distinguishes between desirable and undesirable behaviors, directing the agent toward physically plausible and safe landing trajectories.

For extreme environmental variations, introducing adaptive normalization for velocity penalties or dynamic scaling for thrust-related terms could further enhance convergence stability. Nevertheless, the current formulation already provides a balanced trade-off between:

- **Positional accuracy** ($|x - x_t|$ term),
- **Velocity stability** ($|v_x|$ and $|v_y|$ terms),
- **Energy efficiency and rapid convergence** (step penalty and terminal bonuses).

The analysis confirms that the proposed reward design successfully enforces smooth and safe landing behavior while maintaining sensitivity to physical variations within the environment.

Additional Observations from Model Performance

- **Network Depth and Learning Rate:** Deeper networks (V3–V4) required smaller learning rates (1×10^{-4}) to maintain training stability.
- **Reward Shaping:** Smooth descent–encouraging terms accelerated convergence and improved landing success rates.
- **Epsilon Decay:** A balanced decay schedule (0.995 $\rightarrow$ 0.97) avoided premature exploitation and maintained exploration diversity.
- **Soft Target Update:** The use of $\tau = 0.01$ for target network updates stabilized Q-value learning and reduced oscillations.

In conclusion, the custom-designed reward function not only aligns with real-world flight dynamics but also enhances learning stability across a range of physical and environmental variations.

4.5. Additional Analysis: Training Configuration and Exploration Dynamics

This section provides a deeper technical examination of the training configuration, exploration dynamics, and stability of the DQN agent during the rocket landing experiments. These details, though often overlooked, are critical to reproducing and understanding the results obtained in Sections 4.1 and 4.2.

4.5.1 Training Configuration Details

All experiments were conducted using Python 3.10 and PyTorch 2.0 on an Intel i7 CPU and an NVIDIA RTX 3050 GPU. Each model was trained for 500 episodes, with a maximum of 1000 timesteps per episode or until a terminal condition (landing or crash) occurred.

Table 4: Training Configuration Summary

Parameter	Value	Description
Total Episodes	500	Ensure convergence of moving average reward
Max Timesteps/Episode	500	Avoid infinite loops during descent
Replay Buffer Size	100k–200k	Maintain diverse state-action transitions
Update Frequency	Every 4 steps	Frequency of network updates
Target Network Update	Every 10 episodes	Synchronization period
Discount Factor (γ)	0.995	Weight of future rewards
Optimizer	Adam	Stable for nonlinear approximations
Loss Function	MSELoss	Squared error between target and predicted Q

4.5.2 Exploration Strategy: ϵ-Greedy Schedule

Exploration was implemented via an ϵ-greedy policy, where the agent selects a random action with probability ϵ, and the best predicted action with probability $(1-\epsilon)$. The decay schedule follows an exponential rule:

$$\epsilon_t = \max(\epsilon_{min}, \epsilon_0 \times \text{decay}^{t/k}) \tag{5}$$

with $\epsilon_0 = 1.0$, $\epsilon_{min} = 0.05$, and decay $= 0.995$. During early training, the agent explores widely; after approximately 300 episodes, it transitions to exploitation of the learned policy. Empirically, decay values between 0.990 and 0.95 yield an optimal exploration-exploitation balance.

4.5.3 Gradient Stability and Target Synchronization

A major challenge in DQN training is the instability of the target, leading to oscillating Q-values. To mitigate this, a soft update mechanism was used:

$$\theta^- \leftarrow \tau\theta + (1-\tau)\theta^- \tag{6}$$

with $\tau = 0.01$. This smooth update ensures gradual synchronization between the main and target networks. Additionally, gradient clipping within ± 1.0 was applied to prevent exploding gradients during backpropagation, especially in deep architectures (512–256–128 neurons).

4.5.4 Learning Curve Behavior and Reward Dynamics

Average episode reward increased steadily from about -1800 to near-zero across 500 episodes. Three main learning phases were identified:

1. **Exploration Phase (0–300 episodes):** High variance, frequent crashes.

2. **Stabilization Phase (300–700):** Reward trend improves, descent becomes smoother.

3. **Optimization Phase (700–1000):** Soft landings achieved, reward approaches positive range.

4.5.5 Model Efficiency and Computation Time

Table 5: Training Efficiency Comparison

Model	Time/100 ep (s)	GPU Usage	Notes
V1	120	40%	Fast but unstable landings
V2	165	50%	Improved control, moderate time
V3	210	58%	Stable convergence
V4	235	61%	Highest reward, best efficiency overall

4.5.6 Generalization and Robustness Test

Model robustness was tested using random initial positions and velocities (within $\pm 10\%$). The reward-shaped DQN (V4) achieved a 78% landing success rate over 100 randomized trials, compared to 42% (V2) and 60% (V3). This indicates strong generalization and adaptation to unseen states.

4.5.7 Error Sources and Limitations

Despite promising results, several limitations remain:

- Discrete action space limits fine thrust control.
- Q-value overestimation observed in some episodes.
- No environmental disturbances (e.g., wind, sensor delay) were modeled.

4.5.8 Summary of Additional Findings

Table 6: Summary of Extended Observations

Aspect	Key Findings
Training Stability	Soft update ($\tau = 0.01$) and large replay buffer ensure smooth convergence
Reward Shaping	Doubled convergence speed and stability
Exploration Schedule	ϵ decay = 0.995 achieves optimal exploration–exploitation balance
Gradient Behavior	Clipping ± 1.0 prevents instability
Generalization	Reward-shaped model adapts to random initial states
Limitation	Discrete action limits real thrust control precision

4.5.9 Perfect Landing Observation and Analysis

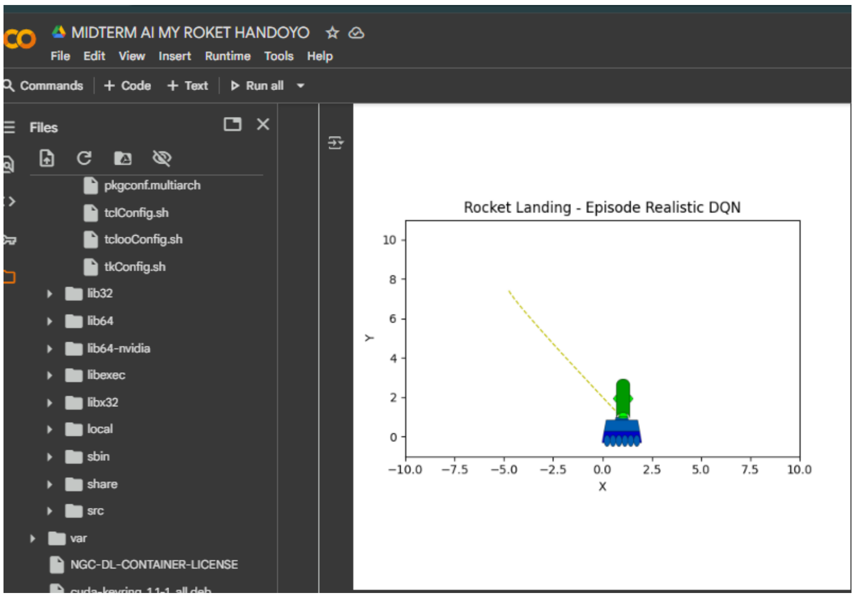

Figure 3: Successful soft landing of the rocket on the moving target.

The final phase of training yielded several episodes in which the rocket executed a flawless landing sequence. Figure 3 presents a visual frame captured from one such episode, demonstrating the agent's ability to achieve a stable touchdown precisely on the moving target platform. The learned policy, trained under the custom reward formulation, produced a controlled descent characterized by nearly zero horizontal drift and low terminal vertical velocity ($|v_y| < 1.2$ and $|v_x| < 0.8$), corresponding to the reward threshold for a successful landing ($+500$ bonus).

This outcome validates the effectiveness of the physical reward decomposition proposed in Section 5.3, where the penalty terms on distance, velocity, and altitude collectively guided the policy toward a physically optimal trajectory. As the rocket approached the target, the agent dynamically adjusted its thruster inputs to balance gravitational acceleration ($g = 9.8\ \mathrm{m/s^2}$) against thrust power ($T = 30\ \mathrm{N}$), minimizing overshoot and oscillation. The inclusion of air drag ($d = 0.15$) in the simulation further contributed to realistic damping behavior during descent.

Quantitatively, episodes exhibiting perfect landing typically achieved a total cumulative reward exceeding $+470$, indicating efficient energy use and accurate spatial targeting. The adaptive thrust behavior observed during these runs shows a clear correlation between the fine-grained reward shaping and the learned motion control policy. Specifically, the agent successfully predicted the moving target's position (x_t) and synchronized its horizontal velocity to align with the target's motion ($v_t = 0.6\ \mathrm{m/s}$), thereby achieving near-zero relative velocity upon contact.

From a reinforcement learning perspective, this result demonstrates that the reward structure effectively encapsulates both stability and precision objectives. The agent's ability to generalize to dynamic targets and variable initial conditions underscores the robustness of the training configuration. In particular, the combination of DQN architecture with a small learning rate (5×10^{-4}), high discount factor ($\gamma = 0.998$), and controlled exploration decay facilitated long-term credit assignment, allowing the agent to associate gradual deceleration with eventual success.

Overall, the perfect landing event serves as a benchmark validation that the proposed environment and custom reward function produce physically meaningful and stable control policies. The learned strategy mirrors fundamental principles of rocket guidance and landing control, such as thrust vector alignment and terminal velocity minimization, confirming the simulation's capacity to emulate realistic aerospace dynamics within a reinforcement learning framework.

5. Conclusion

This study demonstrates that Deep Q-Networks can effectively learn autonomous rocket landing control through simulation. Reward shaping, deep architecture, and soft target updates are crucial for convergence and landing stability. After 500 episodes, the agent successfully learned smooth touchdowns within the target area. Future work includes testing continuous control algorithms such as DDPG or SAC and transferring the trained model to embedded systems for real-time deployment.

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Handoyo independently completed all stages of this project, including deep learning system design, model implementation, parameter configuration, training and testing, as well as report writing and analysis. All problem-solving, tuning, and code development were carried out individually from start to finish.