

The biggest computational bottleneck —

the one most likely to **consume time due to arithmetic (e.g., multiplication), looping, and frequency.**

Candidate for Biggest Bottleneck:

Q-value Update Equation inside the Q_Learning() loop:

```
q_value = (1 - self.alpha) * self.Q[(i,j,action)] + self.alpha *  
(reward + self.gamma * self.Q[nxtStateAction])
```

Why THIS is the most expensive bottleneck:

1. Frequent Execution:

- This line is executed **on every step** (i.e., every single move the agent makes per episode).
- If each episode has ~10–20 steps and there are 10,000 episodes → **100,000–200,000+ evaluations.**

2. Arithmetic-heavy:

- Involves **multiple multiplications and additions**:
 - `self.alpha * (...)`
 - `self.gamma * Q[...]`
 - Plus intermediate additions.

3. Memory Access (Q-table lookups):

- **2 dictionary accesses per update**:
 - `self.Q[(i,j,action)]`
 - `self.Q[nxtStateAction]`
 - These are hashed lookups and can have some overhead.
-

Breakdown of Computation:

Expanded:

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

q_value =

$(1 - \alpha) * Q[s, a]$ \leftarrow [1 multiplication]
 $+ \alpha * (\text{reward} + \gamma * Q[s', a'])$ \leftarrow [2 multiplications + 1 addition]

Total:

- 3 multiplications

- 2 additions

- 2 dictionary accesses (Q-table)

Over thousands of steps, **this becomes the most compute-heavy operation** in the entire code.

Can It Be Optimized?

Yes, but not dramatically. Some micro-optimizations:

- We can try using HW

Final Verdict:

 **Biggest bottleneck =**

$q_value = (1 - \alpha) * Q[(i,j,\text{action})] + \alpha * (\text{reward} + \gamma * Q[\text{nxtStateAction}])$
because it's **multiplication-heavy, frequently executed**, and involves **costly dictionary access**.

Let me know if you'd like to benchmark it or optimize it with Numba or NumPy.

a **hardware (HW) accelerator** can significantly speed this up, especially for embedded systems or FPGA-based simulators.

Proposal: Hardware Accelerator for Q-value Update

Target Expression:

We want to accelerate this:

$$q_value = (1 - \alpha) * Q[s, a] + \alpha * (reward + \gamma * Q[s', a'])$$

This involves:

- **3 float multiplications**
 - **2 float additions**
 - **A max-value computation loop**
-

Implementation Options:

We'll target **FPGA or custom ASIC** implementation with **fixed-point arithmetic** for better efficiency (float is expensive in hardware).

1. Datapath Design:

Inputs:

- $Q_current \rightarrow Q(s, a)$
- $Q_next[] \rightarrow Q(s', a')$ for all a'
- α (alpha)
- γ (gamma)
- reward (immediate reward)

Control Logic:

- FSM that:
 1. Loops through $Q_next[]$ to find \max_Q_next

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

2. Computes:
3. $\text{temp1} = \gamma \times \text{max_Q_next}$
4. $\text{temp2} = \text{reward} + \text{temp1}$
5. $\text{temp3} = \alpha \times \text{temp2}$
6. $\text{temp4} = (1 - \alpha) \times \text{Q_current}$
7. $\text{Q_new} = \text{temp3} + \text{temp4}$

Modules:

- Floating-point or fixed-point **Multiplier** × 2
 - Floating-point or fixed-point **Adder** × 2
 - **Max Finder** for looping through 4 Q-values
 - **Register file** for Q-table storage (can be dual-port BRAM in FPGA)
-

2. Fixed-point Format Suggestion:

- Use **Q8.8** or **Q4.12** format (depending on precision vs. resource tradeoff)
 - 16-bit fixed-point gives decent range for reward values from -5 to +1 and learning rate terms
-

3. Finite State Machine (FSM) Controller:

States:

- IDLE
 - FIND_MAX_Q_NEXT → loop to find max of 4 Q[s', a']
 - COMPUTE_TEMP → do all intermediate computations
 - WRITE_BACK → write updated Q back into BRAM/register
 - DONE
-

4. Performance Boost Estimate (FPGA):

Assuming:

- Clock @ 100 MHz

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

- Each Q-update taking ~10–15 cycles

Estimated throughput:

- ~6.6 million Q-updates/sec
- Compared to software Q-update: ~100k–300k/sec on CPU

✅ ~20x–60x speedup possible

🔌 5. Integration Options:

- **Standalone accelerator** for Q-update module (called by main CPU/MCU)
 - **Tightly coupled** coprocessor in embedded SoC (e.g., RISC-V + Q-accelerator)
 - **Verilog/VHDL module** synthesized in FPGA using tools like Vivado or Intel Quartus
-

📦 Optional Enhancements:

- Add **Q-table caching** to reduce read/write delay
 - Use **streaming AXI interface** to connect with a system memory bus
 - Add support for **batch Q-updates** (pipeline multiple Q-value updates)
-

```

graph TD
    A["Q[s,a]"] --> B["Register / BRAM Interface"]
    B --> C["MAX Finder"]
    D["Q[s',a']"] --> C
    E["loop 4 a'"] --> C
    C --> F["Arithmetic"]
    G["reward"] --> F
    H["alpha, gamma"] --> F
    F --> I["Pipeline"]
    I --> J["Updated Q-value"]
  
```

The flowchart illustrates the Q-learning algorithm's data flow:

- Input:** $Q[s,a]$ is fed into the **Register / BRAM Interface**.
- MAX Finder:** This block receives $Q[s',a']$ and iterates over a' (indicated by "loop 4 a'") to find the maximum value.
- Arithmetic:** The output from the MAX Finder and the **reward** are processed here, along with parameters α and γ .
- Pipeline:** The result from the Arithmetic block is passed through a pipeline.
- Output:** The final result is the **Updated Q-value**.

SystemVerilog (SV) implementation of the **Q-value update accelerator**. It targets the core expression:

$$Q_{\text{new}} = (1 - \alpha) * Q_{\text{current}} + \alpha * (\text{reward} + \gamma * \max Q_{\text{next}})$$

This code assumes **fixed-point arithmetic** (16-bit, Q4.12 format) and is structured for clarity, using an FSM for the datapath control.



Key Modules in This SV Code:

- A **max_q_finder** to find the max of 4 next-state Q-values.
- A **q_update_core** module to compute the Q-value update.
- A **testbench interface** can be built later to simulate and integrate.



q_update_core.sv — Q-value Update Accelerator (Q4.12 Fixed-Point)

```
module q_update_core (
    input  logic      clk,
    input  logic      rst,
    input  logic      start,
    input  logic signed [15:0] Q_current,
    input  logic signed [15:0] Q_next_0,
    input  logic signed [15:0] Q_next_1,
    input  logic signed [15:0] Q_next_2,
    input  logic signed [15:0] Q_next_3,
    input  logic signed [15:0] reward,
    input  logic signed [15:0] alpha,
    input  logic signed [15:0] gamma,
    output logic signed [15:0] Q_new,
    output logic      done
);

    typedef enum logic [1:0] {
```

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

```
        IDLE,
        FIND_MAX,
        COMPUTE,
        DONE
    } state_t;

    state_t state, next_state;

    logic signed [15:0] max_q_next;
    logic signed [31:0] temp1, temp2, temp3, temp4, temp5;
    logic signed [31:0] one_minus_alpha;

    always_ff @(posedge clk or posedge rst) begin
        if (rst)
            state <= IDLE;
        else
            state <= next_state;
    end

    always_comb begin
        next_state = state;
        case (state)
            IDLE:      if (start) next_state = FIND_MAX;
            FIND_MAX:  next_state = COMPUTE;
            COMPUTE:   next_state = DONE;
            DONE:      next_state = IDLE;
        endcase
    end

    // Max Q[s', a']
    always_ff @(posedge clk) begin
        if (state == FIND_MAX) begin
```


Frozen Lake Analysis: Challenge 10

Satyajit Deokar

```
        if (Q_next_1 > max_q_next) max_q_next <= Q_next_1;
        if (Q_next_2 > max_q_next) max_q_next <= Q_next_2;
        if (Q_next_3 > max_q_next) max_q_next <= Q_next_3;
    end
end

// Q-update computation (Q4.12 fixed point)
always_ff @(posedge clk) begin
    if (state == COMPUTE) begin
        one_minus_alpha <= (16'h1000 - alpha); // 1.0 in
Q4.12 = 0x1000
        temp1 <= (gamma * max_q_next) >>> 12; //  $\gamma$  *
max_Q_next
        temp2 <= reward + temp1[15:0]; // reward +  $\gamma$ 
* max_Q_next
        temp3 <= (alpha * temp2[15:0]) >>> 12; //  $\alpha$  *
(reward +  $\gamma$  * max_Q_next)
        temp4 <= (one_minus_alpha * Q_current) >>> 12; // (1-
 $\alpha$ ) * Q_current
        temp5 <= temp3 + temp4; // final Q_new
    end
end

// Output & done flag
always_ff @(posedge clk) begin
    if (state == DONE) begin
        Q_new <= temp5[15:0];
    end
end

assign done = (state == DONE);

endmodule
```

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

Notes:

- **Fixed-point format:** Q4.12 \rightarrow 4 integer bits, 12 fractional bits.
 - 1.0 = 0x1000
 - >>> 12 used to normalize after multiplication.
 - Can be connected to a Q-table memory (RAM/BRAM) externally.
 - Assumes start signal triggers a single update operation.
-

Example Input Encodings (Q4.12 format):

Value Q4.12 Hex

1.0 0x1000

0.5 0x0800

0.9 0x0E66

0.1 0x0199

-5.0 0xF000

Frozen Lake Analysis: Challenge 10

Satyajit Deokar

block diagram to understand

