Imitation Learning for Aerial Agents

Environment: Unreal Engine 5 w/AirSim

Dimitrios Yfantidis (3938)

Evangelos Spatharis (3949)

Inspiration and First Thoughts (I)

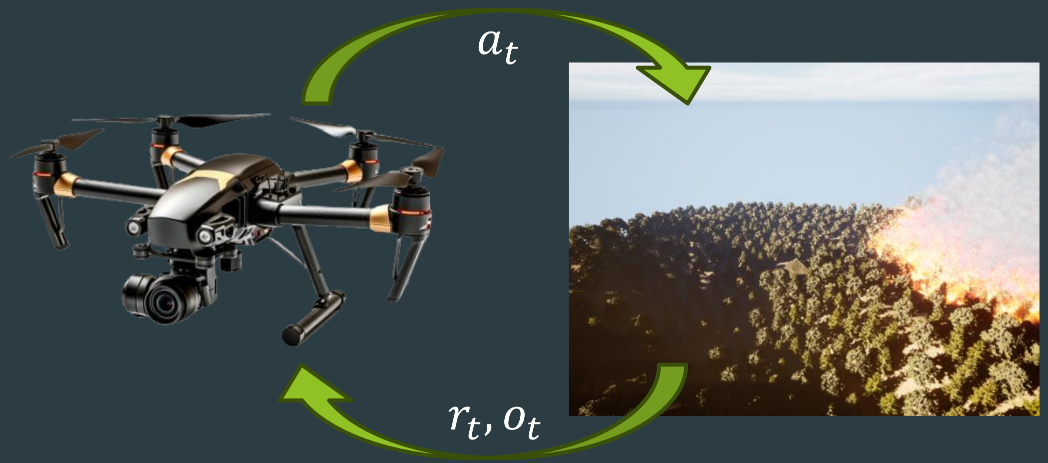
“Why use Unreal Engine?”

- Derived from our personal interest for Computer Graphics.
- Familiarity with 3D περιβάλλοντα and tools such as game/physics engines.
- Willingness to contribute to the solution of complex real-world problems (with respect to the corresponding specifications).
- Computer Simulations: fundamental element of Reinforcement Learning.

Inspiration and First Thoughts (I)

"Why use Unreal Engine?"

- Derived from our personal interest for Computer Graphics.
- Familiarity with 3D περιβάλλοντα and tools such as game/physics engines.
- Willingness to contribute to the solution of complex real-world problems (with respect to the corresponding specifications).
- Computer Simulations: fundamental element of Reinforcement Learning.



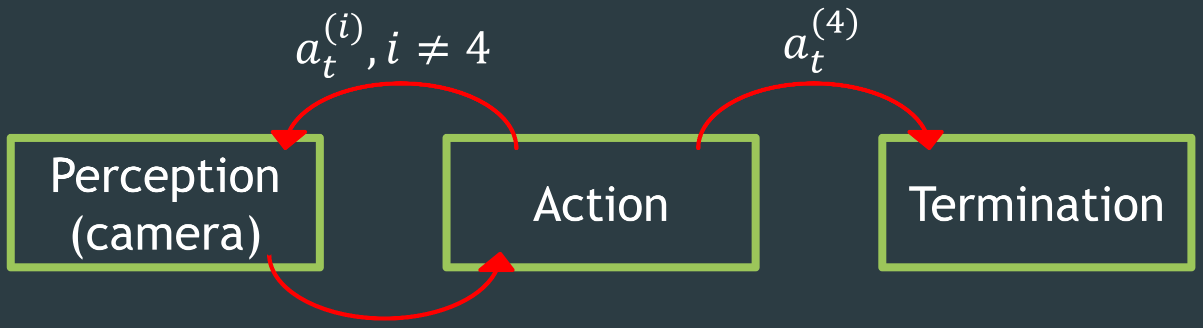
Inspiration and First Thoughts (II)

"Why focus on Unmanned Aerial Vehicles (UAVs)?"

- Microsoft's AirSim library offers convenient connectivity between Python scripts and 3D environments such as Unreal Engine environments.
- UAVs are widely used in a plethora of applications in the emergency planning and disaster management sector such as a) sensing and locating forest fires and b) search and rescue operation –among others.
- This specific software pipeline had already well-established foundations from a previous researcher's work.

The Problem (I)

- The drone is placed in an Unreal environment which depicts a natural scenery (mainly a forest).
- In this environment, a small fire is placed in a tree which starts spreading to nearby trees. After a specific, finite amount of time, the fire will have levelled either most of the forest or all of it.
- At the same time, the drone uses its camera to locate any hints of smoke or fire. Furthermore, it can roam freely within the environment towards any direction.
- The procedure is completed successfully when the drone both locates the fire and approaches it at a sufficiently close distance.



Δράσεις	Περιγραφή
$a_t^{(0)}$	"Approaching"
$a_t^{(1)}$	"Stepping Back"
$a_t^{(2)}$	"Moving Right"
$a_t^{(3)}$	"Moving Left"
$a_t^{(4)}$	"Finished"

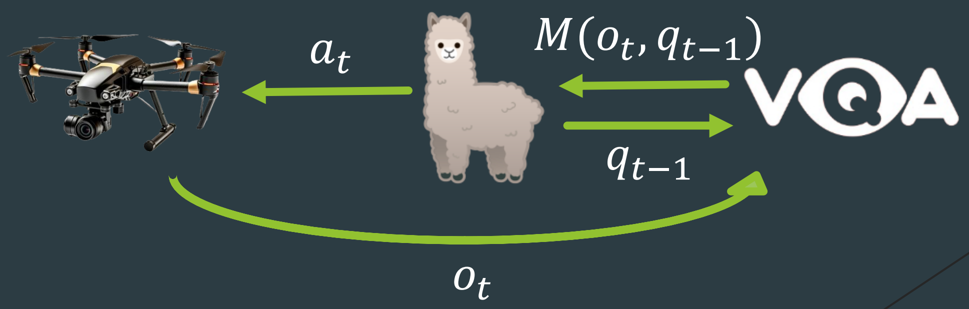
The Problem (II)

- How could such a drone be trained to trace and tack down the fire using only its camera and changing its position (in an alternating manner)?

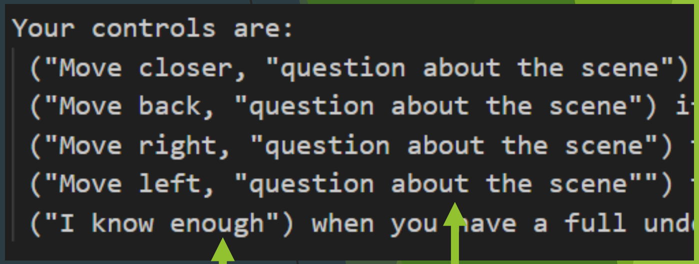
System of Neural Networks (I)

- Multimodal Language Model (MLM), $M : O \times T^* \rightarrow T^*$
  - ✓ Input: Image $\{0, 1, \ldots, 255\}^{WxHx3}$ → Output: Image description (text)
  - ✓ Responsible for the UAV's perception.
  - ✓ A linguistic description is attributed to what its camera observes.
  - ✓ The Visual Question Answering (VQA) μοντέλο LAVIS by Salesforce was used for this task.
- Large Language Model (LLM), $L_1 : T^* \rightarrow A,\ L_2 : T^* \rightarrow T^*$
  - ✓ Processes the description derived by the MLM based on which it decides the next action.
  - ✓ The LLM's decisions are regarded as optimal, and thus the training's ground truth.
  - ✓ The models that were used for this were Microsoft's Phi3-mini (initially) and Meta's LLaMa3 (afterwards).

$$a_t = L_1\big(M(o_t)\big)$$
$$q_t = L_2\big(M(o_{t-1})\big)$$

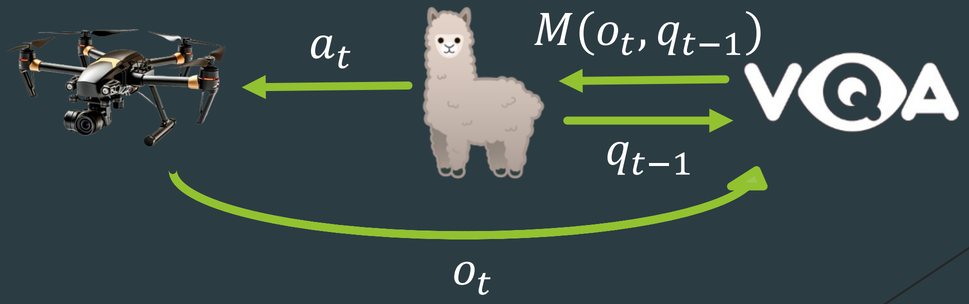


System of Neural Networks (I)



- Multimodal Language Model (MLM), $M : O \times T^* \to T^*$
  - ✓ Input: Image $\{0, 1, \dots, 255\}^{WxHx3}$ → Output: Image description (text)
  - ✓ Responsible for the UAV's perception.
  - ✓ A linguistic description is attributed to what its camera observes.
  - ✓ The Visual Question Answering (VQA) μοντέλο LAVIS by Salesforce was used for this task.
- Large Language Model (LLM), $L_1 : T^* \to A$, $L_2 : T^* \to T^*$
  - ✓ Processes the description derived by the MLM based on which it decides the next action.
  - ✓ The LLM's decisions are regarded as optimal, and thus the training's ground truth.
  - ✓ The models that were used for this were Microsoft's Phi3-mini (initially) and Meta's LLaMa3 (afterwards).

$$a_t = L_1(M(o_t))$$
$$q_t = L_2(M(o_{t-1}))$$

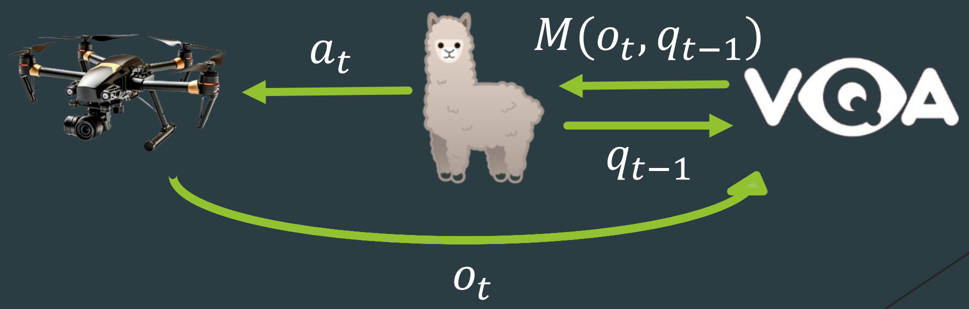


System of Neural Networks (I)

```
Your controls are:
 ("Move closer, "question about the scene")
 ("Move back, "question about the scene") i
 ("Move right, "question about the scene")
 ("Move left, "question about the scene"")
 ("I know enough") when you have a full und
```

- Multimodal Language Model (MLM), $M : O \times T^* \rightarrow T^*$
  - ✓ Input: Image $\{0, 1, \ldots, 255\}^{WxHx3}$ → Output: Image description (text)
  - ✓ Responsible for the UAV’s perception.
  - ✓ A linguistic description is attributed to what its camera observes.
  - ✓ The Visual Question Answering (VQA) μοντέλο LAVIS by Salesforce was used for this task.
- Large Language Model (LLM), $L_1 : T^* \rightarrow A,\ L_2 : T^* \rightarrow T^*$
  - ✓ Processes the description derived by the MLM based on which it decides the next action.
  - ✓ The LLM’s decisions are regarded as optimal, and thus the training’s ground truth.
  - ✓ The models that were used for this were Microsoft’s Phi3-mini (initially) and Meta’s LLaMa3 (afterwards).

Unquantized: ~16GB
Quantized: ~9.5GB

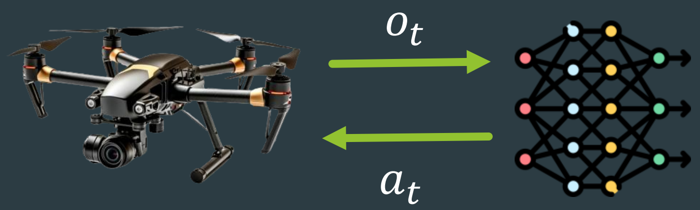


Unquantized: ~8GB
Quantized: ~4.5GB

System of Neural Networks (II)

- This system can locate the fire and translate the drone towards it.
- Obviously, a drone cannot be equipped with large scale deep neural networks with billions of parameters in real world applications as it is a real-time system with computational time and memory restrains.
- Utility of a new neural network, $f^* : O \to A$, of realistic memory size and data inference speed which performs an equivalent functionality:

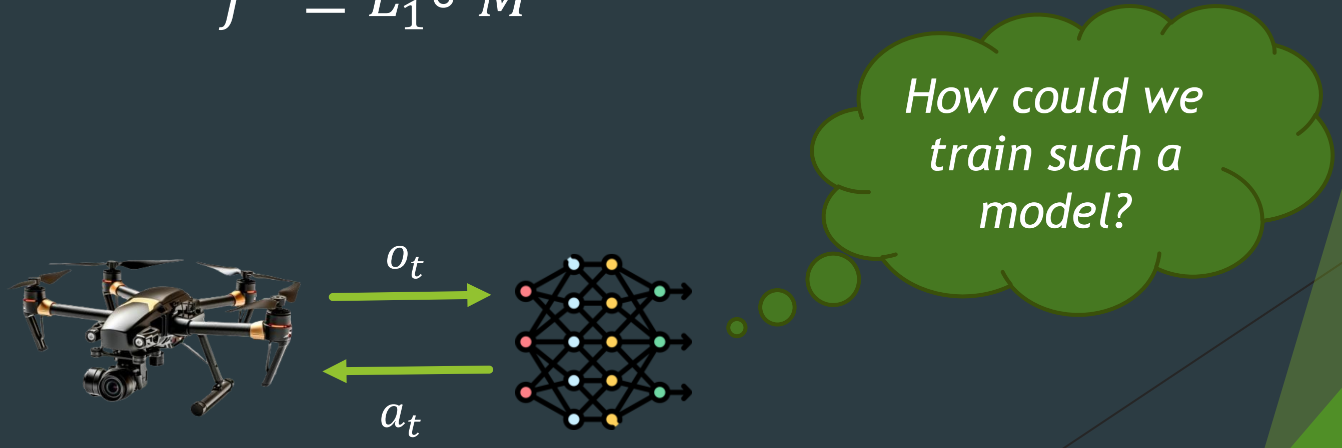
$$f^* \equiv L_1 \circ M$$



System of Neural Networks (II)

- This system can locate the fire and translate the drone towards it.
- Obviously, a drone cannot be equipped with large scale deep neural networks with billions of parameters in real world applications as it is a real-time system with computational time and memory restrains.
- Utility of a new neural network, $f^* : O \to A$, of realistic memory size and data inference speed which performs an equivalent functionality:

$$f^* \equiv L_1 \circ M$$

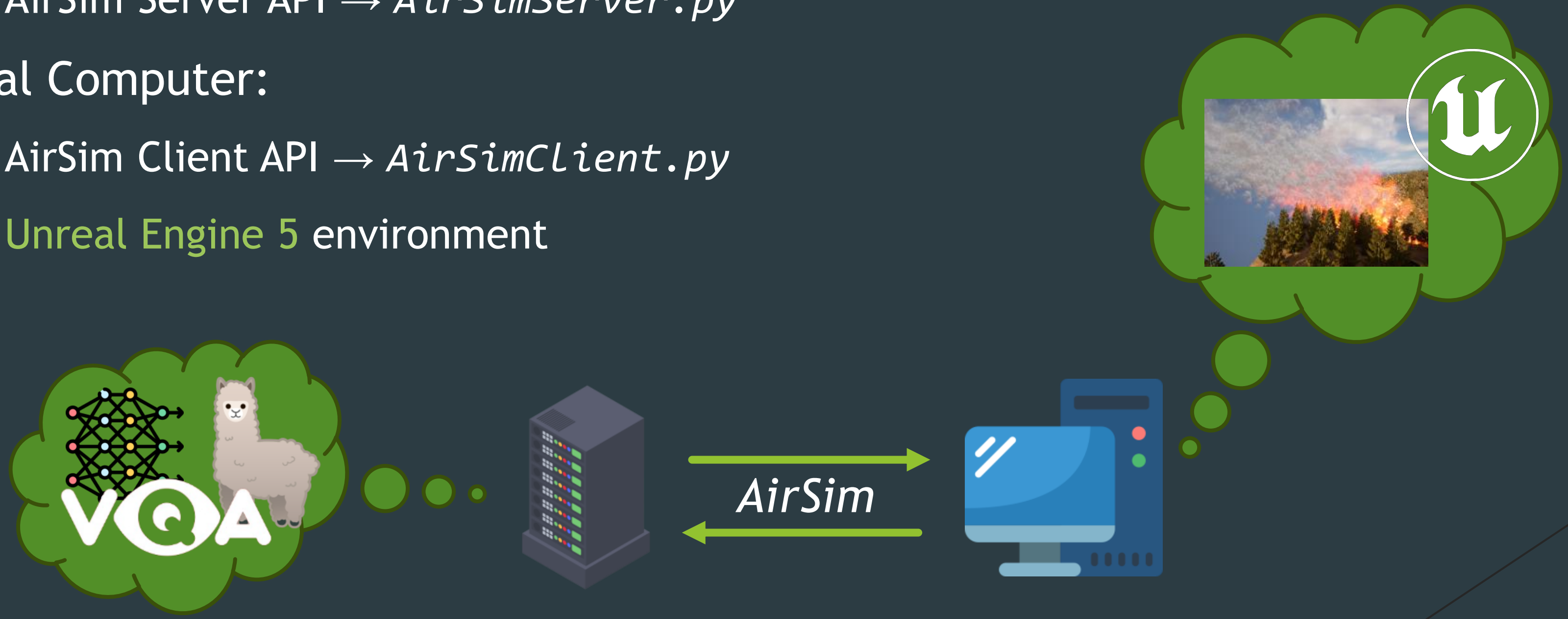


Our Distributed System

- Remote computer, $2 \times$ RTX 4090 24GB = 48GB VRAM:
  - ✓ Large Language Model and VQA → *llm_server.py, llm_client.py, llm_init.py, VQAWrapper.py, vqallm.py*
  - ✓ RL Agent and Deep Q-Network → *Agent.py*
  - ✓ AirSim Server API → *AirSimServer.py*

Our Distributed System

- Remote computer, $2 \times$ RTX 4090 24GB = 48GB VRAM:
  - ✓ Large Language Model and VQA → *llm_server.py, llm_client.py, llm_init.py, VQAWrapper.py, vqallm.py*
  - ✓ RL Agent and Deep Q-Network → *Agent.py*
  - ✓ AirSim Server API → *AirSimServer.py*
- Local Computer:
  - ✓ AirSim Client API → *AirSimClient.py*
  - ✓ Unreal Engine 5 environment



Deep Reinforcement Learning (I)

- Representation of the UAV as an RL Agent.
- The reward, r_t, is equal to -1 if $f(o_t) \neq L_1\left(M\left(o_t,\ L_2(M(o_{t-1}))\right)\right)$, else 0.
- Thus, our aerial agent is trained from the knowledge derived from the multimodal and the large language models.
- However, the learning process is not supervised as this would not be compatible with the core idea behind reinforcement learning.
- The agent's training method is the classic Deep Q-Network (DQN) algorithm with slight variations.

Deep Reinforcement Learning (II)

- Constructing the agent and loading it on the GPU.
- Training for 25 episodes with training evaluation afterwards.

```
drone = UnrealDroneAgent(
    env=AirSimEnv(),
    device=torch.device("cuda:0")
)
EXEC_INFO = { 'num_checkpoints' : 1, 'num_episodes' : 25 }


for checkpoint in range(EXEC_INFO['num_checkpoints']):
    # Enter training mode
    drone.log(">>>>>> Now entering TRAINING mode <<<<<<", color, Colors.purple)
    drone.train(num_episodes=EXEC_INFO['num_episodes'])
    # Reset the LLM's context window
    end_train_msg = drone.env.teacher.llm.ask("!CHAT_RESET")
    drone.log(end_train_msg, color, Colors.orange)
    # Enter evaluation mode
    drone.log(">>>>>> Now entering EVALUATION mode <<<<<<", color, Colors.purple)
    drone.test()
    # Reset the LLM's context window
    end_test_msg = drone.env.teacher.llm.ask("!CHAT_RESET")
    drone.log(end_test_msg, color, Colors.orange)
# Shut down LLM
drone.env.teacher.llm.disconnect()
```

Deep Reinforcement Learning (II)

- Constructing the agent and loading it on the GPU.
- Training for 25 episodes with training evaluation afterwards.

```
drone = UnrealDroneAgent(
    env=AirSimEnv(),
    device=torch.device("cuda:0")
)
EXEC_INFO = { 'num_checkpoints' : 1, 'num_episodes' : 25 }


for checkpoint in range(EXEC_INFO['num_checkpoints']):
    # Enter training mode
    drone.log(">>>>>> Now entering TRAINING mode <<<<<<", color, Colors.purple)
    drone.train(num_episodes=EXEC_INFO['num_episodes'])
    # Reset the LLM's context window
    end_train_msg = drone.env.teacher.llm.ask("!CHAT_RESET")
    drone.log(end_train_msg, color, Colors.orange)
    # Enter evaluation mode
    drone.log(">>>>>> Now entering EVALUATION mode <<<<<<", color, Colors.purple)
    drone.test()
    # Reset the LLM's context window
    end_test_msg = drone.env.teacher.llm.ask("!CHAT_RESET")
    drone.log(end_test_msg, color, Colors.orange)
# Shut down LLM
drone.env.teacher.llm.disconnect()
```

Restarting the LLM by deleting its context window.

Deep Reinforcement Learning (III)

- The environment computes a new state.
- For simplicity we assume that $s_t \equiv o_t$, i.e. the camera input describes the state of the world perfectly even if the environment is not fully observable (*read more*).

```
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ * θ + (1 − τ) * θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Deep Reinforcement Learning (IV)

- Choosing and action $f(o_t) = a_t^{(i)} \in$ A

```
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ θ + (1 − τ) θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Deep Reinforcement Learning (V)

- With probability $1-\varepsilon_t$ the agent decides on its own the (what it considers to be) the optimal solution based on its policy network.

```
def select_action(self, state: torch.Tensor):
    # Value between [0, 1)
    sample = random.random()
    eps_threshold = self.EPS_END + (self.EPS_START - self.EPS_END) * \
        math.exp(-1. * self.steps_done / self.EPS_DECAY)
    self.steps_done += 1
    if sample > eps_threshold:
        with torch.no_grad():
            # t.max(1) will return the largest column value of each row.
            # second column on max result is index of where max element was
            # found, so we pick action with the larger expected reward.
            return self.policy_net(state).max(1).indices.view(1, 1)
    else:
        return torch.tensor([[self.env.teacher.ask(False)[1]]], device=self.device, dtype=torch.long)
```

Deep Reinforcement Learning (VI)

- With probability $1 - \varepsilon_t$ the agent decides on its own the (what it considers to be) the optimal solution based on its policy network.
- Otherwise, the agent leaves it on the large models to decide with probability ε_t.

```python
def select_action(self, state: torch.Tensor):
    # Value between [0, 1)
    sample = random.random()
    eps_threshold = self.EPS_END + (self.EPS_START - self.EPS_END) * \
        math.exp(-1. * self.steps_done / self.EPS_DECAY)
    self.steps_done += 1
    if sample > eps_threshold:
        with torch.no_grad():
            # t.max(1) will return the largest column value of each row.
            # second column on max result is index of where max element was
            # found, so we pick action with the larger expected reward.
            return self.policy_net(state).max(1).indices.view(1, 1)
    else:
        return torch.tensor([[self.env.teacher.ask(False)[1]]], device=self.device, dtype=torch.long)
```

Avoids the early change of state.

Deep Reinforcement Learning (VII)

- The environment transitions to a new state, which it returns along with the reward/punishment, r_t.

```python
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ * θ + (1 − τ) * θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Deep Reinforcement Learning (VIII)

- This new experience is stored in the Replay Buffer for future training.

```
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ * θ + (1 − τ) * θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Deep Reinforcement Learning (IX)

- Train the policy network.

```
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ * θ + (1 − τ) * θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Deep Reinforcement Learning (IX)

- Train the policy network.

```python
def optimize_model(self) -> None:
    if len(self.memory) < self.BATCH_SIZE:
        return
    transitions = self.memory.sample(self.BATCH_SIZE)
    # Transpose the batch. This converts batch-array of Transitions to Transition of batch-arrays.
    batch = UnrealDroneAgent.Transition(*zip(*transitions))
    # Compute a mask of non-final states and concatenate the batch elements
    # (a final state would've been the one after which simulation ended)
    non_final_mask = torch.tensor(tuple(map(lambda s: s is not None,
                                            batch.next_state)), device=self.device, dtype=torch.bool)
    non_final_next_states = torch.cat([s for s in batch.next_state
                                                if s is not None])
    state_batch = torch.cat(batch.state)
    action_batch = torch.cat(batch.action)
    reward_batch = torch.cat(batch.reward)
    # Compute Q(s_t, a) - the model computes Q(s_t), then we select the columns of actions taken.
    # These are the actions which would've been taken for each batch state according to policy_net
    state_action_values = self.policy_net(state_batch).gather(1, action_batch)

    # Compute V(s_{t+1}) for all next states.
    # Expected values of actions for non_final_next_states are computed based
    # on the "older" target_net; selecting their best reward with max(1).values
    # This is merged based on the mask, such that we'll have either the expected
    # state value or 0 in case the state was final.
    next_state_values = torch.zeros(self.BATCH_SIZE, device=self.device)
    with torch.no_grad():
        next_state_values[non_final_mask] = self.target_net(non_final_next_states).max(1).values
    # Compute the expected Q values
    expected_state_action_values = (next_state_values * self.GAMMA) + reward_batch

    # Compute Huber loss
    criterion = nn.SmoothL1Loss()
    loss = criterion(state_action_values, expected_state_action_values.unsqueeze(1))

    # Optimize the model
    self.optimizer.zero_grad()
    loss.backward()
    # In-place gradient clipping
    torch.nn.utils.clip_grad_value_(self.policy_net.parameters(), 100)
    self.optimizer.step()
```

Deep Reinforcement Learning (X)

- Train the policy network.
- Train the target network.

```
def train(self, num_episodes: int):
    for i_episode in range(num_episodes):
        # Initialize the environment and get its state
        state, info = self.env.reset()
        state = torch.tensor(state, dtype=torch.float32, device=self.device).unsqueeze(0)
        for t in count():
            action = drone.select_action(state)
            screenshot, reward, terminated, truncated, _ = self.env.step(action.item())
            reward = torch.tensor([reward], device=drone.device)
            done = terminated or truncated
            next_state = None if terminated else torch.tensor(screenshot, dtype=torch.float32, device=self.device).unsqueeze(0)
            # Store the transition in memory
            self.memory.push(state, action, next_state, reward)
            # Move to the next state
            state = next_state
            # Perform one step of the optimization (on the policy network)
            self.optimize_model()
            # Soft update of the target network's weights
            # θ′ ← τ * θ + (1 − τ) * θ′
            target_net_state_dict = self.target_net.state_dict()
            policy_net_state_dict = self.policy_net.state_dict()
            for key in policy_net_state_dict:
                target_net_state_dict[key] = policy_net_state_dict[key] * self.TAU + target_net_state_dict[key] * (1-self.TAU)
            self.target_net.load_state_dict(target_net_state_dict)
            if done:
                # self.episode_durations.append(t + 1)
                # self.plot_durations()
                break
```

Experiments and Results (I)

```
[21:02:43] vqa said :
Answer: Answer: ['a blurry image of the sky over some cattle.']
Caption: [Caption: [['a blurry image of the sky over some cattle']] 0.9]
[21:02:44] llm answer : [21:02:44] "Move closer, "Are there any people or vehicles in the scene?"
```

```
[21:02:44] Agent's action: Move closer
```

Experiments and Results (II)

```
[21:02:46] vqa said :
Answer: Answer: ['closer,']
Caption: [Caption: [['a camera - view photograph of a desert area with a mountain distant']] 0.9]
[21:02:47] llm answer : [21:02:47] "Move closer, "What is the terrain like in this desert area?"
```

```
[21:03:04] Agent's action: Move closer
```

Experiments and Results (III)

```
[21:03:06] vqa said :
Answer: Answer: ['closer,']
Caption: [Caption: [['a large cluster of large red lights in a video game']] 0.9]
[21:03:07] llm answer : [21:03:07] "Move back, "Are there any objects or structures in the desert area that could be related to the red lights?"
```

```
[21:03:22] Agent's action: Move right
```

Πειράματα και Αποτελέσματα (IV)

```
[21:03:21] vqa said :
Answer: Answer: ['no']
Caption: [Caption: [['a image in forest blazing on fires fireworks fire fire, oil fire fire fire fire']] 0.9]
[21:03:22] llm answer : [21:03:22] "Move right, "Is there a fire or flames in the desert area?"
```

```
[21:03:41] Agent's action: Move right
```

Πειράματα και Αποτελέσματα (V)

```
[21:03:25] vqa said : Answer:
Answer: ['right,']
Caption: [Caption: [['fire in fire explosion bonfire fire red fire fire fire flames the a this fire fire']] 0.9]
[21:03:26] llm answer : [21:03:26] "Move right, "Is there anyone or anything near the fire that could be in danger?"
```

```
[21:04:00] Agent's action: Move left
```

Experiments and Results (VI)

```
[21:03:40] vqa said :
Answer: Answer: ['move right,']
Caption: [Caption: [['a fire is raging with flames on fire']] 0.9]
[21:03:41] llm answer : [21:03:41] "Move right, "Are there any people or animals near the fire that could be hurt?"
```

```
[21:04:18] Agent's action: I know enough
[21:05:03] Chat has been reset at the end of episode #0
```

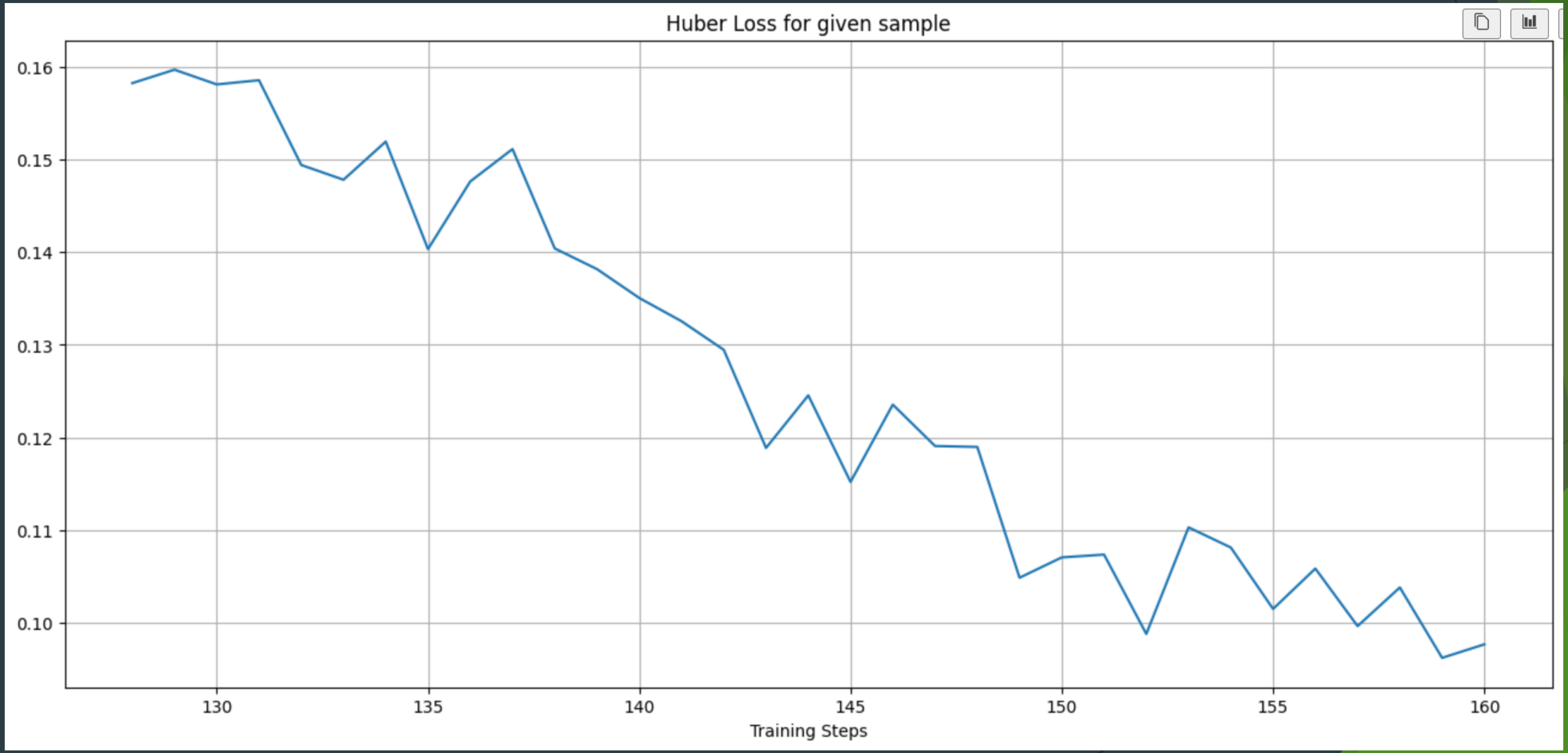
Experiments and Results (VII)

- The next episode starts and the process is repeated.

```
[21:02:38] >>>>>> Now entering TRAINING mode <<<<<<
[21:02:38] reset train start
[21:02:40] reset train end
[21:02:44] Agent's action: Move closer
[21:03:04] Agent's action: Move closer
[21:03:22] Agent's action: Move right
[21:03:41] Agent's action: Move right
[21:04:00] Agent's action: Move left
[21:04:18] Agent's action: I know enough
[21:05:03] Chat has been reset at the end of episode #0
[21:05:03] reset train start
[21:05:05] reset train end
[21:05:08] Agent's action: Move closer
[21:05:23] Agent's action: Move closer
[21:05:41] Agent's action: Move back
[21:05:59] Agent's action: Move left
[21:06:22] Agent's action: Move right
[21:06:45] Agent's action: I know enough
[21:07:31] Chat has been reset at the end of episode #1
[21:07:31] reset train start
[21:07:33] reset train end
[21:07:36] Agent's action: Move closer
[21:07:59] Agent's action: Move right
[21:08:17] Agent's action: Move left
[21:08:32] Agent's action: Move closer
[21:08:52] Agent's action: Move closer
[21:09:09] Agent's action: I know enough
[21:09:54] Chat has been reset at the end of episode #2
[21:09:54] Chat has been reset
[21:09:54] >>>>>> Now entering EVALUATION mode <<<<<<
```

Experiments and Results (VIII)

- In the following graph we can see the development of the loss function with respect to time (Huber Loss). It is computed after each renewal step.



Suggestions for Future Research

- Further quantization of the models, or at least the LLaMa3 one's.
- Transitioning to more powerful RL algorithms of higher accuracy such as PPO.
- Improvement of the reward mechanism (reward shaping).
- Add LSTM neurons to integrate sequential patterns as this specific problem is based sequential data.
- Fine-tuning the hyperparameters of the Teacher και Agent instances.
- Appropriate increasing of the action space (e.g. $\pm 90^\circ$ rotation command).
- Replacement of Salesforce LAVIS with Phi3-Vision.
- This project is distributed to different computers and different conda environments. The accumulation of the entire project's code in the same machine is suggested, as well as the improvement of the interoperability between the different local runtime environments.

Suggestions for Future Research (I)

- Further quantization of the models, or at least the LLaMa3 one's.
  - ✓ The models take up a sizeable part of VRAM.
  - ✓ Explicit cleaning of the CUDA cache memory is considered, but the models' trend for increasing their size is ever-growing.
  - ✓ This obstructs the execution of the program for an increased time period, e.g. 10000 episodes.
  - ✓ This is, however, the realistic time period after which the agent will, theoretically, start to exhibit increase in its performance.

```
[21:05:03] GPU usage
[21:05:03]  > cuda:0 usage: 11720/24564 MiB
[21:05:03]  > cuda:1 usage: 6446/24564 MiB
[21:05:07] Context Window: Discarding interaction
[21:05:07] [('127.0.0.1', 45844)] prompted with a message of 127 characters
[21:05:07] Prompt type: <class 'str'>
[21:05:07] > Prompt size: 2893
[21:05:07] > Pipeline size: 48
[21:05:08] Prompt processed after 0.742 seconds)
[21:05:08] GPU usage
[21:05:08]  > cuda:0 usage: 12078/24564 MiB
[21:05:08]  > cuda:1 usage: 6990/24564 MiB
[21:05:10] Context Window: Saving interaction
[21:05:10] [('127.0.0.1', 45844)] prompted with a message of 111 characters
[21:05:10] Prompt type: <class 'str'>
[21:05:10] > Prompt size: 3056
[21:05:10] > Pipeline size: 48
[21:05:11] Prompt processed after 0.618 seconds)
[21:05:11] GPU usage
[21:05:11]  > cuda:0 usage: 12154/24564 MiB
[21:05:11]  > cuda:1 usage: 7020/24564 MiB
[21:05:25] Context Window: Saving interaction
[21:05:25] [('127.0.0.1', 45844)] prompted with a message of 143 characters
[21:05:25] Prompt type: <class 'str'>
[21:05:25] > Prompt size: 3346
[21:05:25] > Pipeline size: 48
[21:05:26] Prompt processed after 0.803 seconds)
[21:05:26] GPU usage
[21:05:26]  > cuda:0 usage: 12224/24564 MiB
[21:05:26]  > cuda:1 usage: 7094/24564 MiB
[21:05:40] Context Window: Discarding interaction
[21:05:40] [('127.0.0.1', 45844)] prompted with a message of 127 characters
```

Suggestions for Future Research (II)

- Transitioning to more powerful RL algorithms of higher accuracy such as PPO.
  - ✓ Avoids the algorithm's hypersensitivity to changes in hyperparameters → Stability.
  - ✓ Online learning → Avoids storing past experiences in the Replay Buffer → Increased efficiency in space and training time.
  - ✓ Features prior knowledge of the rewards → Increased performance.

Algorithm 1 PPO, Actor-Critic Style

for iteration$=1, 2, \ldots$ **do**
  for actor$=1, 2, \ldots, N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ in environment for T timesteps
    Compute advantage estimates $\hat{A}_1, \ldots, \hat{A}_T$
  end for
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$
  $\theta_{\text{old}} \leftarrow \theta$
end for

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t\left[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)\right]$$

$$r_t(\theta) = \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)},$$

Suggestions for Future Research (III)

- Improvement of the reward mechanism (reward shaping).
  - ✓ The current reward mechanism is probably too simplistic for the task at hand.
  - ✓ Not enough attention has been paid to improving its implementation as, so far, it is considered a detail and not an essential part of the logic of the wider project.
  - ✓ In the future, however, the improvement of reward shaping is a function of vital importance for the quality of the results and the speed of convergence of the algorithm.

Suggestions for Future Research (IV)

- Add LSTM neurons to integrate sequential patterns as this specific problem is based sequential data.
  - ✓ As mentioned before, the environment is partially observable and not fully observable, so the simplification of the form $s_t = f(o_t)$ applied is not allowed.
  - ✓ The agent must pay attention to the path he is following, not just the given snapshot.
  - ✓ Usage of recurrent architecture → The state is now defined as:

$$s_t = f(o_1, o_2, \ldots, o_t)$$

similar to the case of the A3C Labyrinth problem.

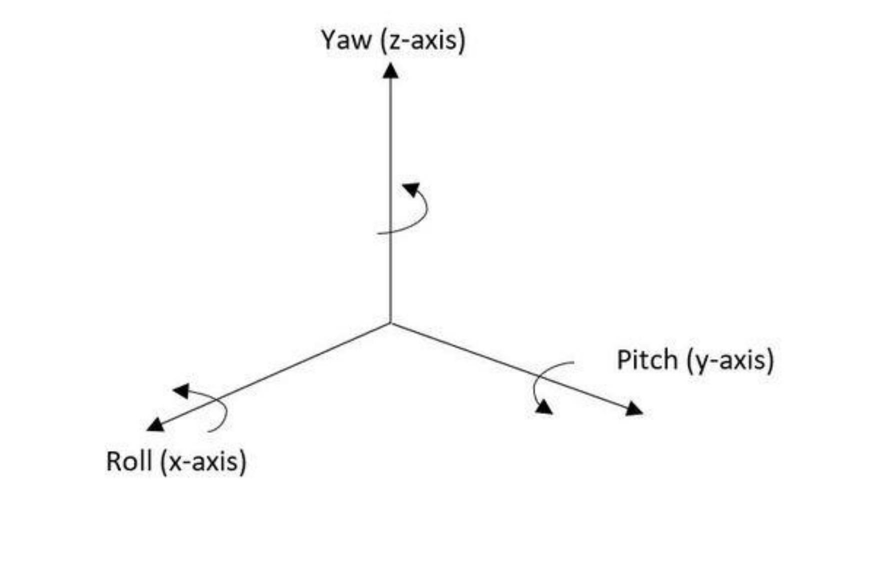
Suggestions for Future Research (V)

- Fine-tuning the hyperparameters of the Teacher και Agent instances.
  - ✓ The default values are:

```
batch_size: int = 128,
gamma: float = 0.99,
eps_start: float = 0.9,
eps_decay: float = 1000.0,
eps_end: float = 0.05,
tau: float = 5e-3,
learning_rate: float = 1e-4,
replay_buffer_size: int = 10000,
```

Suggestions for Future Research (VI)

- Appropriate increasing of the action space (e.g. $\pm 90°$ rotation command).
  - ✓ At the moment, the drone only features actions for changing its position but not its orientation.
  - ✓ The existence of an option to change angles (mainly yaw) would greatly increase the agent's capabilities.



Suggestions for Future Research (VII)

- Replacement of Salesforce LAVIS with Phi3-Vision.
  - ✓ In general, LAVIS's way of speaking is a bit strange (unprocessed, raw language).
  - ✓ In its answers it may repeat words or simply ramble nonsense.

```
Answer: Answer: ['a bright bright orange fire blazing from the sky.']
 Caption: [Caption: [['it is a bright bright orange fire blazing from the sky']] 0.7541]
Move forward "What you do"
Answer: Answer: ['act in the same way as the fireman you are protecting.']
 Caption: [Caption: [['a big fire is coming out of the trees']] 0.9341]
Move forward "What you do"
Answer: Answer: ['an fire and fire brush']
 Caption: [Caption: [['large stop a an a a an fire and fire brush fire fire oil landscape a']] 0.6961]
Move forward "What you do"
```

Suggestions for Future Research (VII)

- Replacement of Salesforce LAVIS with Phi3-Vision.
  - ✓ In general, LAVIS's way of speaking is a bit strange (unprocessed, raw language).
  - ✓ In its answers it may repeat words or simply ramble nonsense.
  - ✓ There is even a special directive in LLM's system prompt to ignore nonsensical answers (presumably because it is a common phenomenon).
  - ✓ A lightweight and possibly more efficient model could be the multimodal version of Microsoft's Phi3.

```
Answer: Answer: ['a bright bright orange fire blazing from the sky.']
 Caption: [Caption: [['it is a bright bright orange fire blazing from the sky']] 0.7541]
Move forward "What you do"
Answer: Answer: ['act in the same way as the fireman you are protecting.']
 Caption: [Caption: [['a big fire is coming out of the trees']] 0.9341]
Move forward "What you do"
Answer: Answer: ['an fire and fire brush']
 Caption: [Caption: [['large stop a an a a an fire and fire brush fire fire oil landscape a']] 0.6961]
Move forward "What you do"
```

Suggestions for Future Research (VIII)

- This project is distributed to different computers and different conda environments. The accumulation of the entire project’s code in the same machine is suggested, as well as the improvement of the interoperability between the different local runtime environments.
  - ✓ The approach of implementing the project on different machines and environments leads to increased overhead.
  - ✓ Communication via internet → latency, program instability.
  - ✓ Use of unorthodox communication programming techniques e.g. "scp" commands (disk communication).
  - ✓ This is because the remote machine's OS (Linux) does not support AirSim as it does not feature a headless mode.

Thank You!

A project by:

Dimitrios Yfantidis (3938)

Evangelos Spatharis (3949)