```
# Cell 1: Deep Q-Network (DQN) Simplified Demonstration
# PYTHON CONCEPT: Dictionaries and Q-Learning Basics
# This is a simplified version of DQN to help understand
class SimpleDQN:
   def __init__(self):
       # Q-table as a dictionary: (state, action) -> valu
       self.q_table = {}
       self.learning_rate = 0.1
       self.discount factor = 0.9
   def get_q_value(self, state, action):
       # Get Q-value for state-action pair, default 0 if
       return self.q_table.get((state, action), 0.0)
   def update(self, state, action, reward, next_state):
       # Simple Q-learning update
       old value = self.get q value(state, action)
       # Q-learning formula simplified
       new_value = old_value + self.learning_rate * (
           reward + self.discount_factor * next_max - old
       self.q_table[(state, action)] = new_value
# Example usage
dqn_agent = SimpleDQN()
state = "position_3_obstacle_ahead"
action = "stop"
reward = 10
next_state = "position_3_clear_path"
# Update Q-values
dqn agent.update(state, action, reward, next state)
print(f"Updated Q-value: {dqn_agent.q_table[(state, action)
→ Updated Q-value: 1.0
# Cell 2: Policy Gradient Simplified Example
# PYTHON CONCEPT: Probability-based Decision Making
import random
class SimplePolicyAgent:
   def __init__(self):
       # Policy as probability distribution
       self.action_probabilities = {
```

## Explain code X



You

Please explain this code.



Gemini

Okay, let's break down this code which demonstrates a simplified version of Federated Learning.

# Cell 4: Simplified Federated Learning Example

This code simulates a basic
Federated Learning system using the
previously defined SimpleDQN (Deep
Q-Network) class.

Core Idea: Federated Learning allows multiple agents (think of them as separate devices or systems) to learn collaborativel, without directly sharing their data. Each agent trains on its own data, then they share their learned knowledge (in this case, Q-values) which gets combined to improve everyone's learning.

#### **Code Explanation:**

SimpleFederatedSystem
 Class:



```
'move': 0.5,
            'stop': 0.5
        self.learning rate = 0.1
    def choose action(self):
        # Choose action based on probabilities
        return random.choices(
            list(self.action probabilities.keys()),
            list(self.action_probabilities.values())
        [0]
    def update_policy(self, action, reward):
        # Simple policy update based on reward
        if reward > 0:
            # Increase probability of successful action
            self.action_probabilities[action] += self.le
            # Normalize probabilities
            total = sum(self.action_probabilities.values
            for action in self.action_probabilities:
                self.action probabilities[action] /= tot
# Example usage
policy_agent = SimplePolicyAgent()
for _ in range(5):
    action = policy agent.choose action()
    reward = 1 if action == 'move' else -1 # Example re
    policy_agent.update_policy(action, reward)
    print(f"Action probabilities: {policy_agent.action_p
→ Action probabilities: {'move': 0.5454545454545454,
     Action probabilities: {'move': 0.5454545454545454,
     Action probabilities: {'move': 0.5454545454545454,
     Action probabilities: {'move': 0.5454545454545454,
     Action probabilities: {'move': 0.5454545454545454,
# Cell 3: Multi-Agent System Demonstration
# PYTHON CONCEPT: Multiple Objects Interaction
# Cell 3: Multi-Agent System Demonstration
# PYTHON CONCEPT: Multiple Objects Interaction
# First, define these supporting components:
class SimpleAgent:
    def __init__(self, world_size):
        self.position = random.randint(0, world size - 1
        self.world_size = world_size
```

```
class SimpleFederatedSystem:
        def __init__(self, num_
            self.agents = [Simp]
                               Use code with caution

    aggregate knowledge(self):

    This is the heart of the
    federated learning process. It
    does the following:

    Collects all unique

           state-action pairs: It
           gathers all the different
           states and actions that
           the agents have
           encountered.
                              닎
all pairs = set()
       for agent in self.agents
           all_pairs.update(age
Use code with caution
    **Averages Q-values:** For e
```

averaged\_q\_table = {}

Use code with caution

for state\_action in all\_|
 values = [agent.q\_tal

averaged\_q\_table'

- \*\*Updates agents:\*\* It updat

for agent in self.agents:

IJ

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```
def sense(self, world):
        return world[self.position]
   def decide(self, observation):
        return 'move' if observation == ' ' else 'stop'
   def act(self, action):
        if action == 'move' and self.position < self.wor</pre>
            self.position += 1
def create world(size):
   return [' ' for _ in range(size)]
# Then, define the main class:
class SimpleMultiAgentSystem:
   def init (self, num agents=3, world size=10):
        self.agents = [SimpleAgent(world_size) for _ in
        self.world_size = world_size
        self.world = create_world(world_size)
   def __init__(self, num_agents=3, world_size=10):
        self.agents = [SimpleAgent(world_size) for _ in
        self.world_size = world_size
        self.world = create_world(world_size)
   def communicate(self, agent_index):
        """Simulate communication between agents"""
       # Get positions of other agents
       other positions = [
            a.position for i, a in enumerate(self.agents
            if i != agent_index
        return other_positions
   def coordinate actions(self):
        """Coordinate actions between agents"""
        for i, agent in enumerate(self.agents):
            # Get information about other agents
            other_positions = self.communicate(i)
            # Simple coordination: don't move if another
            observation = agent.sense(self.world)
            if agent.position + 1 in other_positions:
                action = 'stop'
            else:
                action = agent.decide(observation)
            agent.act(action)
def visualize_multi_agent(world, agent_positions):
```

agent.q table = aver

## Use code with caution

## **◆** 2. Example Usage:

- fed\_system =
   SimpleFederatedSystem(
   Creates an instance of
   the federated system.
- Simulate different
   experiences: Gives
   each agent some initial,
   random Q-values to
   represent their
   individual learning.

for i, agent in enumerate(fed\_ state = f"position\_{i}" action = "move" agent.q\_table[(state, a

## Use code with caution

• Print Q-tables before and after aggregation: Shows the Q-tables of the agents before and after the aggregate\_knowledge() function is called to demonstrate how the knowledge is shared and combined.

```
print("Before aggregation:"\
# ... (printing logic)

fed_system.aggregate_knowled

print("\nAfter aggregation:
# ... (printing logic)
```

```
"""Visualize multiple agents in the world"""
   visualization = "+--" * len(world) + "+\n|"
   for i in range(len(world)):
       if i in agent_positions:
          # Show agent number
          agent_num = agent_positions.index(i) + 1
          visualization += f"{agent_num} |"
       else:
          visualization += f"{world[i]} |"
   visualization += "\n+" + "--" * (len(world) * 2) + "
   return visualization
# Example usage
multi_agent_system = SimpleMultiAgentSystem(num_agents=3
for step in range(5):
   multi_agent_system.coordinate_actions()
   agent_positions = [agent.position for agent in multi
   print(f"\nStep {step + 1}")
   print(visualize_multi_agent(multi_agent_system.world
\rightarrow
    Step 1
    +--+--+--+
    | | | 1 | | | | | | 2 | 3 |
    Step 2
    +--+--+--+
       | | | 1 | | | | 2 | 3 |
    Step 3
    +--+--+--+
    | | | | | 1 | | 2 | 3 |
    Step 4
    +--+--+--+
    | | | | | | 1 | 2 | 3 |
    +--+--+--+
     | | | | | | 1 | 2 | 3 |
```

#### Use code with caution

### In Simple Terms:

Imagine three friends are learning to play a video game. Each friend plays the game on their own and learns which actions are good or bad in different situations (this is like building their individual Q-tables). In Federated Learning, the friends would then come together and discuss what they've learned. They would combine their knowledge and agree on the best strategies for each situation. Then, they would each go back to playing the game with this improved understanding. That's essentially what this code is simulating. I hope this helps!

► Sources

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# PYTHON CONCEPT: Distributed Learning and Averaging
class SimpleFederatedSystem:
    def __init__(self, num_agents=3):
        self.agents = [SimpleDQN() for _ in range(num_ager
    def aggregate_knowledge(self):
        """Simulate federated learning by averaging Q-valu
        # Collect all unique state-action pairs
        all_pairs = set()
        for agent in self.agents:
            all_pairs.update(agent.q_table.keys())
        # Average Q-values across agents
        averaged_q_table = {}
        for state_action in all_pairs:
            values = [
                agent.q_table.get(state_action, 0.0)
                for agent in self.agents
            averaged q table[state action] = sum(values)
        # Update all agents with averaged values
        for agent in self.agents:
            agent.q_table = averaged_q_table.copy()
# Example usage
fed_system = SimpleFederatedSystem(num_agents=3)
# Simulate different experiences
for i, agent in enumerate(fed system.agents):
    state = f"position_{i}"
    action = "move"
    agent.q_table[(state, action)] = random.random()
print("Before aggregation:")
for i, agent in enumerate(fed_system.agents):
    print(f"Agent {i} Q-table:", agent.q_table)
fed_system.aggregate_knowledge()
print("\nAfter aggregation:")
for i, agent in enumerate(fed_system.agents):
    print(f"Agent {i} Q-table:", agent.q_table)
→ Before aggregation:
     Agent 0 Q-table: {('position_0', 'move'): 0.25392396
     Agent 1 Q-table: {('position_1', 'move'): 0.04279733
     Agent 2 Q-table: {('position_2', 'move'): 0.73786326
     After aggregation:
```



```
Agent 0 Q-table: {('position_0', 'move'): 0.08464132
     Agent 1 Q-table: {('position_0', 'move'): 0.08464132
     Agent 2 Q-table: {('position_0', 'move'): 0.08464132
#Cell 5: Training Loop with Different Learning Approache
def compare_learning_approaches(episodes=100):
    """Compare different learning approaches"""
    # Initialize agents
    dqn agent = SimpleDQN()
    policy_agent = SimplePolicyAgent()
    # Training results
    dqn_rewards = []
    policy rewards = []
    for episode in range(episodes):
        # DQN approach
        state = "start"
        dqn total reward = 0
        for _ in range(5):
            action = max(
                ['move', 'stop'],
                key=lambda a: dqn_agent.get_q_value(stat
            )
            reward = random.choice([-1, 1]) # Simplifie
            next_state = f"state_{random.randint(1,5)}"
            dqn_agent.update(state, action, reward, next
            dgn total reward += reward
            state = next state
        # Policy Gradient approach
        policy_total_reward = 0
        for _ in range(5):
            action = policy_agent.choose_action()
            reward = random.choice([-1, 1]) # Simplifie
            policy_agent.update_policy(action, reward)
            policy_total_reward += reward
        dqn_rewards.append(dqn_total_reward)
        policy_rewards.append(policy_total_reward)
        if episode % 10 == 0:
            print(f"\nEpisode {episode}")
            print(f"DQN Average Reward: {sum(dqn_rewards
            print(f"Policy Average Reward: {sum(policy r
```





## Enter a prompt here

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