Atari Breakout DQN Training

1. Check GPU Availability

```
import tensorflow as tf
print("TensorFlow version:", tf.__version__)
print("GPU is", "available" if tf.config.list_physical_devices('GPU') else "NOT available
```

```
TensorFlow version: 2.18.0
GPU is available
```

2. Install Required Packages

```
# Run this cell and restart runtime when prompted
!pip install numpy==1.25.2
!pip install tensorflow==2.15.0
!pip install keras==2.15.0
!pip install h5py==3.11.0
!pip install pillow==10.3.0
!pip install gymnasium[atari]==0.29.1
!pip install keras-rl2==1.0.4
!pip install autorom[accept-rom-license]
!AutoROM --accept-license
```

Show hidden output

3. Install Atari ROMs

```
# Create a directory for saving models
```

4. Mount Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

Show hidden output

Next steps: Explain error

5. keras-rl2 compatibility patch

```
""" This module fixes the compatibility issue between keras-rl2 and gymnasium """
import os
import rl

rl_path = os.path.dirname(rl.__file__)
callbacks_path = os.path.join(rl_path, 'callbacks.py')

with open(callbacks_path, 'r') as file:
    content = file.read()

fixed_content = content.replace(
    'from tensorflow.keras import __version__ as KERAS_VERSION',
    'from keras import __version__ as KERAS_VERSION'
)

with open(callbacks_path, 'w') as file:
    file.write(fixed_content)

print("Fixed!")
```

```
Fixed!
```

6. Implementation

```
import numpy as np
from keras.models import Sequential
from keras.layers import Dense, Flatten, Conv2D, Input
from keras.optimizers.legacy import Adam  # Using legacy optimizer for compatibility
from rl.processors import Processor
from rl.agents.dqn import DQNAgent
from rl.policy import EpsGreedyQPolicy, LinearAnnealedPolicy
from rl.memory import SequentialMemory
import gymnasium as gym
from gymnasium.wrappers import AtariPreprocessing

class GymCompatibilityWrapper(gym.Wrapper):
    """
    Wrapper to make gymnasium compatible with keras-rl while supporting reward shaping.

    This wrapper bridges the Gymnasium API with keras-rl expectations and ensures
    the processor receives terminal state information for proper reward shaping.
    """
```

```
    def __init__(self, env, processor=None):
        super().__init__(env)
        self.processor = processor

    def step(self, action):
        """
        Update step method to match keras-rl output and enhance reward shaping.

        Adds 'done' flag to info dict when episode terminates, allowing the
        processor to apply end-of-episode reward adjustments.
        """
        obs, reward, terminated, truncated, info = self.env.step(action)
        done = terminated or truncated

        # Signal episode termination to processor
        if done and self.processor is not None:
            info['done'] = True

        return obs, reward, done, info

    def render(self):
        """Update render method to match keras-rl"""
        return self.env.render()

    def reset(self, **kwargs):
        """Update reset method to match keras-rl output"""
        obs, _ = self.env.reset(**kwargs)
        return obs

class StackDimProcessor(Processor):
    """
    Custom processor that resolves dimension mismatches and implements reward shaping.

    Reward shaping is designed to mimic human-like motivation in games:
    - Breaking bricks is the primary objective and main source of satisfaction
    - Dying after scoring feels more disappointing than dying without scoring
    - Surviving longer builds anticipation and makes failure more consequential

    These human-like motivational signals help the agent learn faster by providing
    a richer reward landscape while maintaining the proper incentive hierarchy.
    """
    def __init__(self):
        super().__init__()
        self.episode_steps = 0
        self.episode_rewards = 0
        self._is_terminal = False

    def process_observation(self, observation):
        """Return the observation as is"""
        return observation
```

```
    def process_state_batch(self, batch):
        """Fix dimension mismatch between environment obs and model inputs"""
        # If we have a 5D tensor (batch, window_length, height, width, channel)
        if len(batch.shape) == 5:
            # Get dimensions
            batch_size, window_length, height, width, channels = batch.shape

            # Reshape to (batch, height, width, window_length*channels)
            # This stacks the frames along the channel dimension
            return np.reshape(batch, (batch_size, height, width, window_length * channels
        return batch

    def process_reset(self, observation):
        """Reset episode tracking when environment resets"""
        self.episode_steps = 0
        self.episode_rewards = 0
        self._is_terminal = False
        return observation

    def process_reward(self, reward):
        """
        Shape rewards to provide meaningful learning signals between sparse game rewards.

        The shaping follows human motivation patterns:
        1. Breaking bricks remains the dominant reward (1.0 per brick)
        2. Deaths are penalized in proportion to progress made (more progress = more disa
        3. Pure survival without scoring is minimally rewarded (perseverance)

        Since our environment ends episodes on life loss (terminal_on_life_loss=True),
        each "death" is already treated as an episode termination.
        """
        # Track accumulated rewards and steps
        self.episode_rewards += reward
        self.episode_steps += 1

        # Base reward (from breaking bricks)
        shaped_reward = reward

        # Terminal state detection (end of episode/life loss)
        if hasattr(self, '_is_terminal') and self._is_terminal:
            # Calculate end-of-episode adjustment based on progress
            survival_factor = min(1.0, self.episode_steps / 500)  # Normalized survival d

            if self.episode_rewards > 0:
                # If points were scored: penalize death proportionally to progress
                # Higher points and longer survival = more "disappointing" failure
                end_adjustment = -min(0.3, self.episode_rewards * 0.1 * survival_factor)

                # Comment: Just like in real games, dying after scoring well feels worse
                # than dying without scoring. The penalty scales with both score and surv
```

```
            else:
                # If no points: small reward for survival, penalty for quick deaths
                # This mimics the satisfaction of "lasting longer" even without scoring
                end_adjustment = max(-0.1, 0.05 * (survival_factor - 0.5))

                # Comment: Humans feel a small sense of accomplishment for surviving,
                # even without scoring, but only if they survive a reasonable time.

            shaped_reward += end_adjustment

            # Reset episode tracking
            self.episode_steps = 0
            self.episode_rewards = 0
            self._is_terminal = False

        # Clip final reward to standard range
        return np.clip(shaped_reward, -1.0, 1.0)

    def process_info(self, info):
        """Process game information to detect episode termination."""
        # Track terminal state for next reward processing
        if 'done' in info and info['done']:
            self._is_terminal = True
        return info

def make_env(env_id):
    """
    Creates a wrapped Atari environment with reward shaping for faster learning.

    The environment includes human-like motivational signals that help
    the agent learn from sparse rewards by providing a richer feedback landscape.
    """
    env = gym.make(env_id)

    # Apply Atari preprocessing
    env = AtariPreprocessing(
        env,
        noop_max=30,
        frame_skip=4,
        screen_size=84,
        terminal_on_life_loss=True,  # End episode on life loss
        grayscale_obs=True,
        grayscale_newaxis=True,
        scale_obs=False,
    )

    # Create processor for dimension handling and reward shaping
    processor = StackDimProcessor()

    # Make compatible with keras-rl, passing the processor reference
    env = GymCompatibilityWrapper(env, processor)
```

```
    env = GymCompatibilityWrapper(env, processor)

    return env, processor

def model_template(state_shape, n_actions):
    """Defines the DQN model architecture for policy and target networks"""
    model = Sequential()
    model.add(Input(shape=state_shape))
    model.add(Conv2D(32, (8, 8), strides=4, activation='relu'))
    model.add(Conv2D(64, (4, 4), strides=2, activation='relu'))
    model.add(Conv2D(64, (3, 3), strides=1, activation='relu'))
    model.add(Flatten())
    model.add(Dense(512, activation='relu'))
    model.add(Dense(n_actions, activation='linear'))
    return model
```

7. Training Monitor

```
# Training Monitor for efficient Progress Tracking
import matplotlib.pyplot as plt
import pandas as pd
from collections import deque
import time
import datetime
import numpy as np

class TrainingMonitor:
    """
    Memory-efficient training monitor using rolling statistics.

    Tracks metrics using running averages and periodic sampling
    to minimize memory usage and computational overhead.
    """
    def __init__(self, log_dir='/content/drive/MyDrive/breakout_dqn/logs',
                 window_size=100, log_interval=10):
        self.log_dir = log_dir
        self.window_size = window_size
        self.log_interval = log_interval  # Only log every N episodes to CSV
        os.makedirs(log_dir, exist_ok=True)

        # Rolling windows for recent metrics (fixed memory usage)
        self.reward_window = deque(maxlen=window_size)
        self.length_window = deque(maxlen=window_size)
        self.q_window = deque(maxlen=window_size)
        self.loss_window = deque(maxlen=window_size)
        self.sps_window = deque(maxlen=window_size)

        # Running statistics (constant memory regardless of training length)
        self.episode_count = 0
```

```
        self.total_steps = 0
        self.max_reward = float('-inf')
        self.max_reward_episode = 0

        # For checkpoint statistics
        self.checkpoint_episodes = []
        self.checkpoint_rewards = []
        self.checkpoint_steps = []
        self.checkpoint_q_values = []

        # Timing
        self.last_checkpoint_time = time.time()
        self.last_checkpoint_steps = 0

        # Create the CSV log file
        self.log_file = os.path.join(log_dir, 'training_log.csv')
        self.create_log_file()

    def create_log_file(self):
        """Initialize the CSV log file with headers"""
        with open(self.log_file, 'w') as f:
            f.write('episode,total_steps,reward,length,duration,loss,mean_q,epsilon,steps

    def on_episode_end(self, episode, logs):
        """Record metrics at the end of each episode using efficient rolling stats"""
        # Extract metrics
        reward = logs.get('episode_reward', 0)
        steps = logs.get('nb_steps', 0)
        duration = logs.get('duration', 0)
        loss = logs.get('loss', None)
        mean_q = logs.get('mean_q', None)
        epsilon = logs.get('mean_eps', None)
        sps = steps / max(duration, 0.001)  # Steps per second

        # Update counters
        self.episode_count += 1
        self.total_steps += steps

        # Update rolling windows (fixed memory usage)
        self.reward_window.append(reward)
        self.length_window.append(steps)
        self.sps_window.append(sps)

        if loss is not None:
            self.loss_window.append(loss)
        if mean_q is not None:
            self.q_window.append(mean_q)

        # Track maximum reward
        if reward > self.max_reward:
            self.max_reward = reward
```

```
            self.max_reward = reward
            self.max_reward_episode = self.episode_count

        # Log to CSV periodically (not every episode)
        if self.episode_count % self.log_interval == 0:
            with open(self.log_file, 'a') as f:
                f.write(f'{self.episode_count},{self.total_steps},{reward},{steps},{durat

    def on_checkpoint(self, step_count):
        """Generate summary visualizations at checkpoint intervals with minimal data"""
        # Calculate performance
        now = time.time()
        time_elapsed = now - self.last_checkpoint_time
        steps_done = step_count - self.last_checkpoint_steps
        steps_per_sec = steps_done / max(time_elapsed, 0.001)

        # Store checkpoint metrics (minimal data points)
        self.checkpoint_episodes.append(self.episode_count)
        self.checkpoint_rewards.append(self._get_window_avg(self.reward_window))
        self.checkpoint_steps.append(step_count)
        if self.q_window:
            self.checkpoint_q_values.append(self._get_window_avg(self.q_window))

        # Create timestamp for files
        timestamp = datetime.datetime.now().strftime("%Y%m%d_%H%M%S")

        # Create visualizations
        self.generate_plots(step_count, timestamp)

        # Generate summary statistics
        summary = self.generate_summary(step_count, steps_per_sec, time_elapsed)

        # Update checkpoint tracking
        self.last_checkpoint_time = now
        self.last_checkpoint_steps = step_count

        return summary

    def _get_window_avg(self, window):
        """Compute average of a window deque efficiently"""
        if not window:
            return 0
        return sum(window) / len(window)

    def generate_plots(self, step_count, timestamp):
        """Create visualization plots using only checkpoint data and current windows"""
        # Create figure with multiple subplots
        fig, axes = plt.subplots(2, 2, figsize=(15, 12))

        # Plot 1: Episode rewards (using checkpoints and current window)
        ax = axes[0, 0]
```

```
        # Plot checkpoint data (sparse historical data)
        if self.checkpoint_rewards:
            ax.plot(self.checkpoint_episodes, self.checkpoint_rewards, 'b-o', label='Chec

        # Plot recent episodes in detail (from rolling window)
        recent_indices = list(range(self.episode_count - len(self.reward_window) + 1,
                                    self.episode_count + 1))
        ax.plot(recent_indices, list(self.reward_window), 'g-', alpha=0.5, label='Recent

        ax.set_title(f'Episode Rewards (Max: {self.max_reward} at #{self.max_reward_episo
        ax.set_xlabel('Episode')
        ax.set_ylabel('Reward')
        ax.grid(True)
        if self.checkpoint_rewards or self.reward_window:
            ax.legend()

        # Plot 2: Episode lengths (current window only)
        ax = axes[0, 1]
        if self.length_window:
            ax.plot(recent_indices, list(self.length_window))
            ax.set_title(f'Recent Episode Lengths (Avg: {self._get_window_avg(self.length
            ax.set_xlabel('Episode')
            ax.set_ylabel('Steps')
            ax.grid(True)
        else:
            ax.text(0.5, 0.5, 'No episode length data available',
                   horizontalalignment='center', verticalalignment='center')

        # Plot 3: Mean Q-values (checkpoints + current window)
        ax = axes[1, 0]
        if self.checkpoint_q_values:
            ax.plot(self.checkpoint_episodes[len(self.checkpoint_episodes)-len(self.check
                   self.checkpoint_q_values, 'b-o', label='Checkpoint Avg')

        if self.q_window:
            ax.plot(recent_indices, list(self.q_window), 'g-', alpha=0.5, label='Recent E
            ax.set_title(f'Mean Q-Values (Recent Avg: {self._get_window_avg(self.q_window
            ax.set_xlabel('Episode')
            ax.set_ylabel('Q-Value')
            ax.grid(True)
            ax.legend()
        else:
            ax.text(0.5, 0.5, 'No Q-values recorded yet\n(still in warmup phase)',
                   horizontalalignment='center', verticalalignment='center')
            ax.set_title('Mean Q-Values (Not Available)')

        # Plot 4: Training progress (steps vs episodes)
        ax = axes[1, 1]
        if self.checkpoint_episodes:
            ax.plot(self.checkpoint_episodes, self.checkpoint_steps, 'b-o')
```

```
            ax.set_title('Training Progress')
            ax.set_xlabel('Episodes')
            ax.set_ylabel('Total Steps')
            ax.grid(True)

            # Add second y-axis for SPS
            if self.sps_window:
                ax2 = ax.twinx()
                ax2.plot(recent_indices, list(self.sps_window), 'r-', alpha=0.5)
                ax2.set_ylabel('Steps/Second', color='r')
                ax2.tick_params(axis='y', labelcolor='r')
        else:
            ax.text(0.5, 0.5, 'No checkpoint data available yet',
                   horizontalalignment='center', verticalalignment='center')

        plt.tight_layout()

        # Save the figure
        plt.savefig(os.path.join(self.log_dir, f'training_progress_{step_count}_{timestam
        plt.close()

    def generate_summary(self, step_count, steps_per_sec, time_elapsed):
        """Generate checkpoint summary statistics from rolling windows"""
        # Summary statistics use only current windows (constant memory)
        avg_reward = self._get_window_avg(self.reward_window)
        avg_length = self._get_window_avg(self.length_window)
        avg_q = self._get_window_avg(self.q_window) if self.q_window else None

        # Return formatted summary
        summary = {
            'step_count': step_count,
            'episodes_completed': self.episode_count,
            'avg_reward_recent': avg_reward,
            'max_reward_all_time': self.max_reward,
            'avg_episode_length': avg_length,
            'steps_per_second': steps_per_sec,
            'time_elapsed_minutes': time_elapsed / 60
        }

        if avg_q is not None:
            summary['avg_q_value'] = avg_q

        # Save summary to file
        with open(os.path.join(self.log_dir, f'summary_{step_count}.txt'), 'w') as f:
            for key, value in summary.items():
                f.write(f"{key}: {value}\n")

        return summary

    def compare_runs(self, other_log_file, output_path=None):
        """Compare current run with another training run"""
```

```
        try:
            # Load just the necessary data from CSV files (memory efficient)
            current_df = pd.read_csv(self.log_file, usecols=['episode', 'reward'])
            other_df = pd.read_csv(other_log_file, usecols=['episode', 'reward'])

            # Calculate rolling averages
            window = min(100, len(current_df), len(other_df))
            current_df['reward_avg'] = current_df['reward'].rolling(window=window, min_pe
            other_df['reward_avg'] = other_df['reward'].rolling(window=window, min_period

            # Create comparison plot
            plt.figure(figsize=(10, 6))
            plt.plot(current_df['episode'], current_df['reward_avg'], 'b-', linewidth=2,
            plt.plot(other_df['episode'], other_df['reward_avg'], 'r-', linewidth=2, labe
            plt.title('Training Strategy Comparison')
            plt.xlabel('Episode')
            plt.ylabel(f'Avg Reward ({window} ep window)')
            plt.legend()
            plt.grid(True)

            if output_path:
                plt.savefig(output_path)
            plt.show()

            # Return statistics for comparison
            return {
                'current_run': {
                    'episodes': len(current_df),
                    'avg_reward': current_df['reward'].mean(),
                    'max_reward': current_df['reward'].max(),
                    'final_avg': current_df['reward_avg'].iloc[-1] if not current_df.empt
                },
                'comparison_run': {
                    'episodes': len(other_df),
                    'avg_reward': other_df['reward'].mean(),
                    'max_reward': other_df['reward'].max(),
                    'final_avg': other_df['reward_avg'].iloc[-1] if not other_df.empty el
                }
            }

        except Exception as e:
            print(f"Error comparing runs: {e}")
            return None
```

8. Training Function

```
def train_dqn(steps=1000000, save_path='/content/drive/MyDrive/breakout_dqn'):
    """
    Train a DQN agent on Breakout with human-like reward shaping for faster learn
```

```
Train a DQN agent on Breakout with human-like reward shaping for faster learn

Uses reward signals that mimic human motivation in games to accelerate learni
while maintaining proper incentive alignment between objectives.
"""
# Create save directory if it doesn't exist
os.makedirs(save_path, exist_ok=True)

# Initialize memory-efficient training monitor
monitor = TrainingMonitor(
    log_dir=os.path.join(save_path, 'logs'),
    window_size=100,  # Only keep last 100 episodes in memory
    log_interval=10   # Only log every 10 episodes to reduce I/O
)

# Find the latest checkpoint (if any)
latest_step = 0
latest_checkpoint = None

# Regular expression to extract step count from filenames
import re
weight_pattern = re.compile(r'breakout_dqn_weights_(\d+)\.h5')

# Check for existing checkpoint files
if os.path.exists(save_path):
    for filename in os.listdir(save_path):
        match = weight_pattern.match(filename)
        if match:
            step_count = int(match.group(1))
            if step_count > latest_step:
                latest_step = step_count
                latest_checkpoint = os.path.join(save_path, filename)

# Create environment with reward shaping
env, processor = make_env('BreakoutNoFrameskip-v4')

# Set window length for frame stacking
window_length = 4

# Calculate input shape for model
state_shape = (84, 84, window_length)
n_actions = env.action_space.n

# Build DQN model
model = model_template(state_shape, n_actions)
model.summary()

# Use annealed exploration policy for better results
policy = LinearAnnealedPolicy(
    EpsGreedyQPolicy(),
    attr='eps',
```

```
        value_max=1.0,
        value_min=0.1,
        value_test=0.05,
        nb_steps=1000000
    )

    # Configure agent
    memory = SequentialMemory(limit=1000000, window_length=window_length)

    dqn = DQNAgent(
        model=model,
        nb_actions=n_actions,
        memory=memory,
        nb_steps_warmup=50000,
        target_model_update=10000,
        policy=policy,
        enable_double_dqn=True,
        processor=processor  # Use the processor created with the environment
    )

    # Compile DQN agent
    dqn.compile(Adam(learning_rate=0.00025), metrics=['mae'])

    # Load weights if checkpoint exists
    if latest_checkpoint:
        print(f"Found checkpoint at step {latest_step}. Resuming training from {l
        dqn.load_weights(latest_checkpoint)
    else:
        print("No checkpoint found. Starting training from scratch.")
        latest_step = 0

    # Update remaining steps
    remaining_steps = steps - latest_step
    if remaining_steps <= 0:
        print(f"Training already completed ({latest_step} steps). No further trai
        return dqn

    print(f"Training for {remaining_steps} more steps (total target: {steps})")

    # Manual checkpointing
    checkpoint_interval = 100000
    step_count = latest_step

        # Custom training with checkpoints and monitoring
        while step_count < steps:
            # Determine how many steps to train in this batch
            batch_steps = min(checkpoint_interval, steps - step_count)

            # Setup custom callback for monitoring
            class MonitorCallback(keras.callbacks.Callback):
                def on_episode_end(self, episode, logs={}):
```

```
            def on_episode_end(self, episode, logs={}):
                monitor.on_episode_end(episode, logs)

        # Train for a batch of steps
        dqn.fit(env, nb_steps=batch_steps, visualize=False, verbose=2, callba

        # Update step count
        step_count += batch_steps

        # Save checkpoint
        filename = f'breakout_dqn_weights_{step_count}.h5'
        filepath = os.path.join(save_path, filename)
        dqn.save_weights(filepath, overwrite=True)
        print(f"Model saved at step {step_count} to {filepath}")

        # Generate and display checkpoint summary
        summary = monitor.on_checkpoint(step_count)
        print("\n===== TRAINING PROGRESS SUMMARY =====")
        for key, value in summary.items():
            print(f"{key}: {value}")
        print("=====================================\n")

    # Save final model weights
    final_path = os.path.join(save_path, 'breakout_dqn_final.h5')
    dqn.save_weights(final_path, overwrite=True)
    print(f"Final model saved to {final_path}")

    # Final visualization
    timestamp = datetime.datetime.now().strftime("%Y%m%d_%H%M%S")
    monitor.generate_plots(step_count, timestamp)

    env.close()
    return dqn
```

7. Test Fucntion

```
def test_model(weights_path, episodes=5):
    """Test a trained model on Breakout"""
    # Create environment with reward shaping
    env, processor = make_env('BreakoutNoFrameskip-v4')

    # Set window length for frame stacking
    window_length = 4

    # Calculate input shape for model
    state_shape = (84, 84, window_length)
    n_actions = env.action_space.n

    # Build DQN model
```

```
    model = model_template(state_shape, n_actions)

    # Configure agent
    memory = SequentialMemory(limit=10000, window_length=window_length)
    policy = EpsGreedyQPolicy(eps=0.05)  # Low exploration for testing

    dqn = DQNAgent(
        model=model,
        nb_actions=n_actions,
        memory=memory,
        nb_steps_warmup=100,
        target_model_update=10000,
        policy=policy,
        enable_double_dqn=True,
        processor=processor
    )

    # Compile DQN agent
    dqn.compile(Adam(learning_rate=0.00025), metrics=['mae'])

    # Load weights
    dqn.load_weights(weights_path)

    # Test for episodes
    dqn.test(env, nb_episodes=episodes, visualize=True)

    env.close()
```

8. Analytics Dashboard Function

```
def analyze_training_logs(log_path='/content/drive/MyDrive/breakout_dqn/logs/trai
    """
    Generate interactive analytics dashboard from training logs.

    This function loads saved log data and creates visualizations to analyze
    training performance with minimal memory usage.
    """
    try:
        # Load the training log efficiently (only load what we need)
        df = pd.read_csv(log_path)

        # Check if data exists
        if len(df) == 0:
            print("No training data found in log file.")
            return

        # Calculate rolling averages
        window = min(100, len(df))
```

```
df['reward_avg'] = df['reward'].rolling(window=window, min_periods=1).mea
df['length_avg'] = df['length'].rolling(window=window, min_periods=1).mea

if 'mean_q' in df.columns and not df['mean_q'].isna().all():
    df['q_avg'] = df['mean_q'].rolling(window=window, min_periods=1).mear

# Create visualizations
plt.figure(figsize=(15, 12))

# Plot 1: Episode rewards over time
plt.subplot(2, 2, 1)
plt.plot(df['episode'], df['reward'], 'b-', alpha=0.3)
plt.plot(df['episode'], df['reward_avg'], 'r-', linewidth=2)
plt.title('Reward per Episode')
plt.xlabel('Episode')
plt.ylabel('Reward')
plt.grid(True)

# Plot 2: Reward distribution histogram
plt.subplot(2, 2, 2)
plt.hist(df['reward'], bins=20)
plt.axvline(df['reward'].mean(), color='r', linestyle='dashed', linewidtł
plt.title(f'Reward Distribution (Mean: {df["reward"].mean():.2f})')
plt.xlabel('Reward')
plt.ylabel('Count')

# Plot 3: Episode length over time
plt.subplot(2, 2, 3)
plt.plot(df['episode'], df['length'], 'b-', alpha=0.3)
plt.plot(df['episode'], df['length_avg'], 'r-', linewidth=2)
plt.title('Episode Length Over Time')
plt.xlabel('Episode')
plt.ylabel('Steps')
plt.grid(True)

# Plot 4: Q-values over time (if available)
plt.subplot(2, 2, 4)
if 'mean_q' in df.columns and not df['mean_q'].isna().all():
    plt.plot(df['episode'], df['mean_q'], 'b-', alpha=0.3)
    plt.plot(df['episode'], df['q_avg'], 'r-', linewidth=2)
    plt.title('Mean Q-Value Over Time')
    plt.grid(True)
    plt.xlabel('Episode')
    plt.ylabel('Q-Value')
else:
    plt.text(0.5, 0.5, 'No Q-values recorded yet',
            horizontalalignment='center', verticalalignment='center')
    plt.title('Mean Q-Values (Not Available)')

plt.tight_layout()
plt.savefig('/content/drive/MyDrive/breakout_dqn/logs/training_analytics.
```

```
        plt.show()

        # Generate summary statistics
        print("\n===== TRAINING ANALYTICS SUMMARY =====")
        print(f"Total Episodes: {len(df)}")
        print(f"Total Steps: {df['total_steps'].max()}")
        print(f"Average Reward: {df['reward'].mean():.2f}")
        print(f"Max Reward: {df['reward'].max()}")
        print(f"Average Episode Length: {df['length'].mean():.2f}")
        print(f"Last 100 Episodes Average Reward: {df['reward'].tail(100).mean():
        if 'mean_q' in df.columns and not df['mean_q'].isna().all():
            print(f"Average Q-Value: {df['mean_q'].mean():.4f}")
        print("=====================================\n")

        return df
    except Exception as e:
        print(f"Error analyzing logs: {e}")
        return None

def compare_training_strategies(log_path1, log_path2, labels=None, output_path=No
    """
    Compare two different training strategies side by side.

    Args:
        log_path1: Path to first training log CSV
        log_path2: Path to second training log CSV
        labels: Tuple of (label1, label2) for the legend
        output_path: Path to save comparison image
    """
    try:
        # Load logs efficiently
        df1 = pd.read_csv(log_path1)
        df2 = pd.read_csv(log_path2)

        # Use default labels if none provided
        if labels is None:
            labels = ('Strategy 1', 'Strategy 2')

        # Calculate rolling averages
        window = min(100, len(df1), len(df2))
        df1['reward_avg'] = df1['reward'].rolling(window=window, min_periods=1).m
        df2['reward_avg'] = df2['reward'].rolling(window=window, min_periods=1).m

        # Create comparison plot
        plt.figure(figsize=(12, 8))

        # Rewards
        plt.subplot(2, 1, 1)
        plt.plot(df1['episode'], df1['reward_avg'], 'b-', linewidth=2, label=labe
        plt.plot(df2['episode'], df2['reward_avg'], 'r-', linewidth=2, label=labe
        plt.title('Reward Comparison')
```

```
        plt.title('Reward Comparison')
        plt.xlabel('Episode')
        plt.ylabel(f'Avg Reward ({window} ep window)')
        plt.legend()
        plt.grid(True)

        # Episode lengths
        plt.subplot(2, 1, 2)
        df1['length_avg'] = df1['length'].rolling(window=window, min_periods=1).m
        df2['length_avg'] = df2['length'].rolling(window=window, min_periods=1).m
        plt.plot(df1['episode'], df1['length_avg'], 'b-', linewidth=2, label=labe
        plt.plot(df2['episode'], df2['length_avg'], 'r-', linewidth=2, label=labe
        plt.title('Episode Length Comparison')
        plt.xlabel('Episode')
        plt.ylabel('Avg Length (steps)')
        plt.legend()
        plt.grid(True)

        plt.tight_layout()

        if output_path:
            plt.savefig(output_path)
        plt.show()

        # Compare statistics
        print("\n===== TRAINING STRATEGY COMPARISON =====")
        print(f"{labels[0]} vs {labels[1]}")
        print(f"Episodes: {len(df1)} vs {len(df2)}")
        print(f"Final Avg Reward: {df1['reward_avg'].iloc[-1]:.2f} vs {df2['rewar
        print(f"Max Reward: {df1['reward'].max():.1f} vs {df2['reward'].max():.1f
        print(f"Avg Episode Length: {df1['length'].mean():.1f} vs {df2['length'].
        print("========================================\n")

    except Exception as e:
        print(f"Error comparing training strategies: {e}")
```

9. Train the Agent

```
train_dqn(3000000)  # 1M steps for testing, 5M for full training
```

9. Test a Trained Agent

```
test_model('/content/drive/MyDrive/breakout_dqn/breakout_dqn_final.h5')
```

10. Analytics Usage

```
# Example usage after training completes
# Analyze a single training run
analyze_training_logs('/content/drive/MyDrive/breakout_dqn/logs/training_log.csv')

# Example of comparing two different training strategies
# compare_training_strategies(
#     '/content/drive/MyDrive/breakout_dqn_reward_shaping/logs/training_log.csv',
#     '/content/drive/MyDrive/breakout_dqn_baseline/logs/training_log.csv',
#     labels=('With Reward Shaping', 'Baseline DQN'),
#     output_path='/content/drive/MyDrive/breakout_dqn/strategy_comparison.png'
# )
```