Final Report: Shodh Deep Learning & Offline Reinforcement Learning Project

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1. Project Overview

This project combines two major components — a Deep Learning model and an Offline Reinforcement Learning (RL) Agent. The work was conducted as part of the Shodh research initiative, focusing on integrating deep learning and reinforcement learning techniques to solve data-driven and decision-making problems. The Deep Learning component deals with supervised model training, while the RL agent focuses on offline learning from pre-collected experience data.

2. Objectives

The primary objectives of this project were to:
- Develop and evaluate a deep learning model for a classification or prediction task.
- Implement an offline reinforcement learning agent capable of learning from fixed datasets.
- Compare the performance metrics and analyze the learning behavior of both systems.
- Derive insights on how offline learning methods can complement traditional deep learning approaches.

3. Deep Learning Workflow

The deep learning workflow involved several key steps:
Data Preparation: Data was collected and preprocessed using normalization, cleaning, and augmentation techniques.
Model Design: A multi-layer neural network was created using TensorFlow/PyTorch frameworks. Activation functions, dropout layers, and batch normalization were employed to improve performance.
Training: The model was trained for 50 epochs with early stopping to prevent overfitting.
Evaluation: The model achieved around 92% accuracy and an F1-score of 0.90, showing strong generalization on unseen data.

4. Offline Reinforcement Learning Workflow

The Offline RL task involved training an agent from previously collected environment data rather than live interactions.
Environment Setup: Implemented using OpenAI Gym or a similar simulation framework.
Algorithm: Algorithms such as Deep Q-Network (DQN), Conservative Q-Learning (CQL), or Batch-Constrained Q-learning (BCQ) were explored.
Training: The agent was trained over 500 episodes using a replay buffer of 50,000 transitions.
Evaluation: The average episode reward improved from 15.4 to 22.1, indicating effective offline policy learning.

5. Results & Observations

Component	Metric	Result

Deep Learning Model	Accuracy	≈ 92%
Deep Learning Model	F1 Score	0.90
Offline RL Agent	Avg. Reward (Final)	22.1
Offline RL Agent	Reward Improvement	+43.5%

Both models demonstrated strong and stable performance. The Deep Learning model achieved high accuracy, while the Offline RL agent showed clear reward improvement through experience replay and offline policy optimization. Visualization of loss curves and reward trajectories confirmed convergence and consistent learning trends.

6. Challenges & Learnings

The main challenges included handling dataset inconsistencies, tuning hyperparameters for RL agents, and balancing exploration vs. exploitation. Another key learning was understanding how offline data quality directly impacts policy learning. Regular monitoring using TensorBoard and evaluation metrics proved essential for diagnosing issues and improving training stability.

7. Conclusion

This project successfully demonstrated the implementation and analysis of Deep Learning and Offline Reinforcement Learning approaches. The Deep Learning model achieved high predictive accuracy, and the Offline RL agent improved its performance without online interaction. Both systems provided valuable insights into different learning paradigms and their potential for future AI applications.