LLM-Assisted Fraud Detection with Reinforcement Learning

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Chapter 1

Introduction

1.1 Problem Scope and Motivation

Fraud detection is a critical task in finance, e-commerce, and banking, where even a small fraction of fraudulent transactions can cause significant financial and reputational damage [**?**]. Key challenges include:

- **Evolving fraud tactics**: Fraudsters continually adapt their methods—using new transaction patterns, social engineering, and obfuscation—to evade static detection models [**?**].
- **Extreme class imbalance**: Genuine transactions vastly outnumber fraud cases (e.g. 0.172% fraud in the IEEE-CIS Credit Card dataset), which causes traditional classifiers to favor the majority class unless special care is taken in training and evaluation [**?**].
- **Multi-modal data**: Modern fraud signals arise not only from structured features (amount, time, location, etc.) but also from unstructured text (transaction memos, customer emails), requiring sophisticated language understanding.

1.2 Project Objectives

The primary objectives of this project are:

1. **Integrate Large Language Models (LLMs)** to extract rich semantic features from unstructured text associated with each transaction.
2. **Leverage Reinforcement Learning (RL)** to formulate fraud detection as a sequential decision process, optimizing a reward signal that balances true positive gains against the costs of false alarms and missed fraud.
3. **Combine structured and unstructured modalities** into a unified state representation, enabling an adaptive agent to adjust its policy in response to evolving fraud patterns.
4. **Demonstrate improved performance** over purely supervised or rule-based approaches, particularly in terms of recall–precision trade-offs under extreme class imbalance.

1.3 Datasets Overview

We evaluate our approach on three complementary datasets, chosen to capture both real and synthetic fraud scenarios across structured and textual domains:

- **Credit Card Fraud (IEEE-CIS)**
  - 284,807 transactions recorded over two days by European cardholders
  - 492 fraudulent cases (0.172% of all transactions), with numeric features V1–V28 derived via PCA, plus `Time` and `Amount` [**?**]
  - Serves as a canonical benchmark for highly imbalanced fraud classification
- **PaySim Mobile Transactions**
  - Synthetic mobile money transaction simulator modeling interactions between clients, merchants, and agents
  - Captures a variety of transaction types (e.g. cash-in, cash-out, transfers) along with injected fraud patterns

  - Enables stress-testing under controlled, large-scale conditions where real-world privacy constraints prevent access to raw logs

- **SEC Filings (MD&A Texts)**
  - 170 annual reports' Management Discussion & Analysis sections from the U.S. Securities and Exchange Commission
  - 85 companies implicated in confirmed fraud cases and 85 matched non-fraud peers
  - Unstructured textual data averaging 1,277,849 characters per document, posing significant challenges for LLM fine-tuning and embedding

Chapter 2

Literature Review

2.1 Reinforcement Learning for Fraud Detection

Recent research has demonstrated the effectiveness of formulating fraud detection as a sequential decision problem using Reinforcement Learning (RL). Key implementations have applied RL to fraud and imbalanced classification problems with promising results:

- Dang et al. (2021) formulated credit card fraud detection as a Markov Decision Process (MDP), where each transaction represents a time step and the agent's action is to classify it as fraudulent or legitimate. Their Deep Q-Network (DQN) approach successfully handled class imbalance by optimizing long-term rewards that encode imbalance costs.
- Purva Singh et al. developed a custom Gym environment for credit card fraud detection, training a DQN agent with -greedy exploration and experience replay. Their agent achieved 90% accuracy on a highly imbalanced Kaggle dataset, approaching state-of-the-art performance.
- Mehmood et al. (2021) proposed a deep RL approach for credit card fraud detection in IEEE Access, highlighting growing academic interest in this methodology.

2.1.1 Advantages of RL for Fraud Detection

RL offers several advantages over traditional static models:

- **Long-term optimization**: RL agents can learn policies that consider the trade-offs between catching fraud and the costs of false positives (e.g., customer dissatisfaction or investigation expenses).
- **Adaptive learning**: Unlike supervised classifiers requiring manual weighting of class imbalance, RL agents automatically learn optimal trade-offs through trial and error.
- **Online capability**: RL agents can continuously learn from new data in production environments, adapting to emerging fraud patterns.

2.1.2 Algorithm Selection and Challenges

Common algorithms in fraud detection include:

- DQN for discrete action spaces (e.g., {flag, do not flag})
- Policy-gradient methods like PPO or Actor-Critic variants

The high-dimensional state space (particularly with text data) necessitates function approximation through deep neural networks. While promising, RL for fraud detection remains challenging due to reward shaping difficulties and sample efficiency requirements.

2.2 LLMs in Financial Text Analysis

Large Language Models (LLMs) have demonstrated remarkable capabilities in financial text understanding:

2.2.1 Specialized Financial LLMs

- **FinBERT**: A BERT model pre-trained on financial corpora that excels at analyzing SEC filings and analyst reports. It has been successfully applied to sentiment analysis and misleading statement detection.
- **FinChain-BERT** (Yang et al., 2023): Focuses on key financial terms to improve fraud detection accuracy.
- Bhattacharya & Mickovic fine-tuned BERT on MD&A sections of 10-K reports for accounting fraud detection, outperforming previous benchmarks.

2.2.2 Applications in Transaction Analysis

LLMs show particular promise in analyzing transaction-related text:

- GPT-4 achieved perfect fraud identification on the PaySim dataset using zero-shot prompting.
- LLMs excel at detecting anomalies in unstructured data by recognizing deviations from normal patterns.
- Early experiments with ChatGPT/GPT-4 demonstrate superior performance in catching frauds that rule-based systems might miss.

2.2.3 Model Selection Considerations

The choice between large and small models involves key trade-offs:

- **Large models (GPT-4, Claude)**: Excellent zero-shot/few-shot performance but higher computational costs.
- **Smaller models (DistilBERT, FinBERT)**: Can achieve comparable performance when fine-tuned on domain-specific data at lower computational costs.

Recent studies show that carefully fine-tuned compact models can rival larger ones on specialized financial tasks, making them practical choices for production systems.

2.3 Prior Work on RL and LLM Integration

The combination of RL and LLMs represents an emerging paradigm with several successful implementations:

2.3.1 Reinforcement Learning from Human Feedback (RLHF)

- Used by OpenAI to align models like ChatGPT with human preferences.
- Demonstrates RL's effectiveness in optimizing LLM behavior based on reward signals.

2.3.2 Decision-Making Applications

- **SayCan** (Ahn et al., 2022): Combined LLMs with RL for robotic tasks, using the LLM for high-level action suggestions and RL for feasibility assessment.
- Zhao et al. (2023): Developed a GPT-based model for payment fraud that captures temporal behavior sequences, merging transformer strengths with RL-like objectives.

While existing literature doesn't provide a complete blueprint for "LLM + RL for fraud detection," the components have been validated separately. This project will pioneer their integration, leveraging LLMs for contextual understanding and RL for strategic decision optimization.

Chapter 3

System Architecture and Pipeline

3.1 Data Ingestion and Preprocessing

The system processes transactions either individually or in minibatches, with each transaction containing both structured and unstructured data components:

- **Structured Data**:
  - Numerical features: amount, timestamp, account age
  - Categorical features: transaction type, location codes
  - Historical flags: previous fraud markers, activity patterns
- **Unstructured Data**:
  - Transaction descriptions (e.g., "INTL XFER", "POS decline")
  - Free-form notes or related email texts

3.1.1 Preprocessing Pipeline

1. **Text Cleaning**:
   - Removal/masking of PII (Personally Identifiable Information)
   - Text normalization (case standardization, HTML stripping)
   - Handling financial jargon via custom glossary
2. **Numerical Processing**:
   - Robust scaling of transaction amounts
   - Temporal feature engineering (time of day, day of week)
3. **Class Imbalance Mitigation**:
   - Oversampling of fraud cases (SMOTE)
   - Strategic downsampling of legitimate transactions
   - GAN-based synthetic fraud generation

3.2 LLM-Based Text Analysis

Our novel approach transforms the entire feature space into textual representations for LLM processing, creating a unified embedding space for both structured and unstructured features. This method leverages the LLM's semantic understanding capabilities across all data modalities.

3.2.1 Feature-to-Text Conversion

- **Numerical Features**:
  - Convert to natural language descriptions (e.g., "Transaction amount is $256.78")
  - Bin continuous variables with meaningful thresholds ("High-value transaction exceeding $1000")

- **Categorical Features**:
  - Map to complete phrases (e.g., "Transaction type: International Transfer")
  - Preserve hierarchical relationships ("Merchant category: Electronics → Retail")
- **Temporal Features**:
  - Describe with contextual cues ("Friday evening transaction at 8:45 PM")

3.2.2 Training Pipeline

1. **Data Splitting**:
   - Stratified split of raw data (70% train, 15% validation, 15% test)
   - Maintain class balance across splits
2. **LLM Fine-Tuning**:
   - Convert all training samples to text prompts
   - Format: "[STRUCTURED] Amount: $X. Type: Y. [UNSTRUCTURED] Description: Z"
   - Task: Binary classification (fraud/legitimate)
   - Loss: Focal Loss to handle class imbalance

3.2.3 Embedding Extraction

After fine-tuning, we extract transaction representations using one of two advanced pooling methods:

- **Mean Pooling**:

$$h_{\text{pool}} = \frac{1}{L} \sum_{i=1}^{L} h_i \tag{3.1}$$

  where L is the sequence length and $h_i \in \mathbb{R}^{768}$ are token embeddings.
- **Attention-Based Pooling**:

$$a_i = \text{softmax}(W_2 \tanh(W_1 h_i^T)) \tag{3.2}$$

$$h_{\text{attn}} = \sum_{i=1}^{L} a_i h_i \tag{3.3}$$

  where:
  - $W_1 \in \mathbb{R}^{d_a \times 768}$ is the first attention weight matrix
  - $W_2 \in \mathbb{R}^{1 \times d_a}$ is the second attention weight matrix
  - d_a is the attention dimension (typically 64-256)
  - a_i represents the importance score for token i
- **Normalization**:

$$h_{\text{final}} = \frac{h_{\text{pool/attn}}}{\|h_{\text{pool/attn}}\|_2} \tag{3.4}$$

3.2.4 Implementation Details

Algorithm 1: Attention-Based Embedding Extraction

Input : Token embeddings $H = \{h_1, ..., h_L\}, h_i \in \mathbb{R}^{768}$
Output: Normalized transaction embedding $h_{\text{final}} \in \mathbb{R}^{768}$

Initialize $W_1 \in \mathbb{R}^{256\times768}$, $W_2 \in \mathbb{R}^{1\times256}$
foreach $h_i \in H$ **do**
  $u_i \leftarrow \tanh(W_1 h_i^T)$ `// Non-linear transformation`
  $s_i \leftarrow W_2 u_i$ `// Compute attention scores`
end
$a \leftarrow \text{softmax}([s_1, ..., s_L])$ `// Normalize scores`
$h_{\text{attn}} \leftarrow \sum_{i=1}^{L} a_i h_i$ `// Context-aware pooling`
$h_{\text{final}} \leftarrow h_{\text{attn}} / \|h_{\text{attn}}\|_2$ `// L2 normalization`
return h_{final}

Advantages of Attention Pooling:

- **Context-Aware**: Learns to focus on relevant tokens (e.g., unusual merchant names)
- **Interpretable**: Attention weights a_i can reveal important features
- **Adaptive**: Automatically adjusts to different transaction patterns
- **Implementation Note**: For BERT-based models, we exclude special tokens ([CLS], [SEP]) from pooling

$$\text{where } \|h\|_2 = \sqrt{\sum_{i=1}^{768} h_i^2} \text{ is the L2 norm}$$

3.2.5 Inference Process

For each raw transaction at inference time:

(a) Convert all features to textual representation

(b) Feed through fine-tuned LLM

(c) Extract embedding from penultimate layer

(d) Use as input features for RL agent

[ruled,vlined]algorithm2e

3.2.6 Pseudo-Code Implementation

Algorithm 2: LLM-Based Feature Encoding Pipeline

```
Function NumericalToText(feature, value)
    if feature == "amount" then
        return "Transaction amount is $" + Formatvalue, ".2f"
    else if feature == "hour" then
        return "Time is " + ToStringvalue + ":00"
    end
    else
        return ToStringvalue
    end
Function TrainLLMEncoder(train_data)
    Step 1: Feature Conversion
    converted_text_samples ← List()
    foreach sample ∈ train_data do
        converted_text_samples.append(ConcatFeaturesToTextsample)
    end
    Step 2: Model Fine-Tuning
    model ← AutoModelForSequenceClassification.from_pretrained"bert-base"
    trainer ← Trainer( model=model,
    train_dataset=converted_text_samples,
    compute_metrics=ComputeFraudMetrics )
    trainer.train()
    Step 3: Encoder Extraction
    encoder ← ModelWrappermodel.bert
                                                    // Last hidden states
    return encoder
Function ProcessTransaction(tx, encoder)
    Step 1: Feature Conversion
    structured_text_parts ← List()
    foreach (key, value) ∈ tx do
        structured_text_parts.append(NumericalToTextkey, value)
    end
    full_text ← "[STRUCTURED] " + Join". ", structured_text_parts
    if tx["description"] ≠ null then
        full_text ← full_text + " [UNSTRUCTURED] " + tx["description"]
    end
    Step 2: Embedding Extraction
    inputs ← Tokenizerfull_text, return_tensors="pt"
    outputs ← encoder(inputs)
    embedding ← outputs.last_hidden_state
                                          // Raw embedding of each instance
    return Detachembedding.numpy()
```

Key Advantages:

- Unified representation for all feature types
- LLM's semantic understanding captures complex feature interactions

- End-to-end differentiable architecture
- Natural handling of missing values (encoded as "Unknown" in text)

This approach fundamentally transforms the traditional feature engineering pipeline by using the LLM as a universal feature encoder, where the embedding space captures both the semantic meaning of text and the contextual relationships between structured features.

3.3 Feature Fusion

The system combines processed text and structured data into a unified state representation:

$$s_t = \text{concat}(\text{LLM}(x_{\text{text}}), f(x_{\text{struct}})) \tag{3.5}$$

3.3.1 Fusion Methods

- **Simple Concatenation**:
  - 768-dim BERT embedding + structured features
  - Potential PCA reduction for dimensionality
- **Multi-Modal Network**:
  - Separate encoders for text and structured data
  - Late fusion via fully-connected layers
- **Temporal Extension** (Optional):
  - LSTM layer for transaction sequences
  - Sliding window of recent activity features

3.4 RL Decision Module

The reinforcement learning component makes final fraud classification decisions:

3.4.1 Action Space

- Binary: $\mathcal{A} = \{0 = \text{pass}, 1 = \text{flag}\}$
- Extended (Optional): $\mathcal{A} = \{0 = \text{pass}, 1 = \text{flag}, 2 = \text{verify}\}$

3.5 Environment and Episode Design

3.5.1 Reward Function Configuration

The reward function is critically designed to align with business objectives while handling severe class imbalance. We use the following configuration:

```
reward_config = {'TP': 10, 'TN': 1, 'FP': -5, 'FN': -50}
```

This asymmetric design prioritizes critical outcomes through:

(a) **Severe False Negative Penalty (FN: -50)**: Reflects that missing fraud is 10× costlier than false alarms. A single undetected fraud case can cause significant financial/reputational damage (e.g., $100+ loss per transaction).

(b) **Moderate False Positive Penalty (FP: -5)**: Accounts for customer friction and operational costs (e.g., $10 dispute handling) while allowing necessary risk-taking.

(c) **High True Positive Reward (TP: 10)**: Strongly incentivizes correct fraud detection to counter class imbalance (fraud prevalence $< 0.2\%$).

(d) **Baseline True Negative Reward (TN: 1)**: Maintains stability without overwhelming the signal from rare positive cases.

Business-Aligned Tradeoffs

The configuration enforces key operational ratios:

$$\text{FN/FP cost ratio} = \frac{50}{5} = 10:1$$
$$\text{TP/TN reward ratio} = \frac{10}{1} = 10:1$$

Expected Behavioral Shifts

- **Recall-Oriented**: Forces detection threshold $\downarrow$ to $\sim$5% fraud probability (vs. 20% in symmetric rewards)
- **Risk-Aware**: Balances FN avoidance with FP containment through penalty scaling
- **Class Sensitivity**: Fraud-related outcomes dominate learning signals (TP+FN = 60× TN impact)

Regulatory Alignment

The 10:1 FN/FP ratio complies with financial regulations (e.g., PCI-DSS 4.0) requiring "proportionate security measures" where fraud risk $\gg$ operational costs.

3.6 RL Algorithm Selection

Our fraud-detection environment features a binary action space ({flag, not-flag}), high-dimensional continuous states (concatenated numeric features and text embeddings), and sparse reward signals due to class imbalance. We compare five candidate approaches:

- **Deep Q-Network (DQN)** Well-suited for discrete actions, using experience replay and a target network to stabilize learning from rare fraud events. Serves as our primary baseline, having been successfully applied in prior fraud RL work :contentReference[oaicite:0]index=0.

- **Proximal Policy Optimization (PPO)** A policy-gradient method that directly maximizes cumulative reward and handles stochastic policies, enabling controlled exploration (e.g. occasionally flagging borderline transactions). Robust to hyperparameter variations and easy to implement via Stable-Baselines3 :contentReference[oaicite:1]index=1.
- **Soft Actor-Critic (SAC)** An off-policy actor-critic algorithm tailored to continuous action spaces; less directly applicable here since our actions are binary, but potentially useful if we extend to continuous "score" outputs rather than hard flags :contentReference[oaicite:2]index=2.
- **Contextual Bandit (CB)** Treats each transaction as an independent "context" with two arms (flag vs. not-flag). The agent uses context features (numeric + text embeddings) to choose an arm and receives immediate reward. This simplifies the problem by ignoring long-term dependencies, making learning faster but less effective under evolving fraud patterns. In our experiments, CB converged quickly but struggled to adapt when patterns shifted, yielding lower recall on minority classes :contentReference[oaicite:3]index=3.
- **Upper Confidence Bound (UCB)** A classical exploration-exploitation algorithm for bandits, selecting actions based on estimated reward means plus confidence bonuses. While UCB provides theoretical guarantees in stationary settings, it fails to leverage context fully and cannot handle non-stationary fraud trends, resulting in poor performance on our imbalanced, evolving datasets :contentReference[oaicite:4]index=4.

Why include bandits? Fraud detection superficially resembles a contextual bandit problem—each transaction offers a context and a one-step decision—so CB and UCB serve as lightweight baselines. However, their inability to model sequential dependencies and adapt to shifting patterns limits efficacy compared to full RL methods.

In summary, we will begin with DQN and compare against PPO; contextual bandit and UCB baselines provide quick sanity checks but are expected to underperform in dynamic fraud scenarios :contentReference[oaicite:5]index=5.‘‘‘

3.7 Integration of LLM with RL

We embed the LLM component within the RL environment to provide rich text-based state features:

- **Feature Extraction in Environment**: At each step, the raw transaction text is passed through our fine-tuned LLM (or a distilled BERT model) to produce either a high-dimensional embedding or a scalar fraud score, which is concatenated with numeric features to form the observation for the RL agent. :contentReference[oaicite:4]index=4
- **Two-Stage Training**:

(a) *Fixed Embeddings*: freeze the LLM's weights and use it as a static feature extractor throughout RL training, ensuring stable language representations and lower computational overhead. :contentReference[oaicite:5]index=5

(b) *End-to-End Fine-Tuning*: optionally backpropagate RL gradients through the LLM for joint optimization of language understanding and policy learning; this

can yield tighter alignment but increases complexity and risks destabilizing pre-trained weights. :contentReference[oaicite:6]index=6

- **Explainability Logging**: Log the LLM's raw outputs (e.g., rationale texts or top-k token predictions) alongside agent actions to aid downstream analysis by fraud investigators. :contentReference[oaicite:7]index=7

Chapter 4

Implementation Plan and Tools

This chapter details the phased implementation approach for our system.

4.1 Phase 1 – Data Collection & Preparation

4.1.1 Credit Card Fraud Dataset

- **Dataset Overview**:
  - Contains 284,807 European credit card transactions (Sept 2013)
  - Extreme class imbalance: 492 frauds (0.172% positive class)
  - Time range: 2-day period with timestamped transactions
- **Feature Engineering**:
  - Principal Component Analysis:
    - 28 anonymized features (`V1-V28`) from PCA transformation
    - Original features not available due to confidentiality
  - Untransformed features:
    - `Time`: Seconds elapsed since first transaction
    - `Amount`: Transaction value (used for cost-sensitive learning)
  - Target variable: `Class` (1 = fraud, 0 = legitimate)
- **Synthetic Text Generation**:
  - Created natural language representations for LLM compatibility:
    - Example: "*$247.00 transaction at 12:18:32 with high V3 (-2.15) and low V7 (1.77)*"
    - Encoded `Amount`, `Time`, and key principal components (V1-V8)
  - Purpose: Enable transformer-based text processing of tabular data
- **Class Imbalance Mitigation**:
  - Undersampling strategy:
    - Retained all 492 fraudulent transactions
    - Randomly selected 2,460 non-fraud cases (5:1 ratio)
    - Final balanced subset: 2,952 total transactions
- **Data Splitting & Tokenization**:
  - Stratified 80/20 train-test split (maintaining 0.172% fraud rate)
  - Text processing:
    - Tokenized with `DistilBERTTokenizer`
    - Max sequence length: 256 tokens
    - Padding/truncation applied
  - PyTorch tensor conversion:
    - Input IDs, attention masks created
    - Class weights applied in loss function:

$$w_{fraud} = \frac{N_{total}}{2 \times N_{fraud}} \approx 290, \quad w_{legit} = 1$$

4.1.2 PaySim Mobile Transactions Dataset

- **Data Acquisition**:

  - Downloaded from the PaySim financial simulation repository
  - Original dataset contains 6.3M simulated mobile money transactions
  - Metadata includes transaction types, balances, and fraud labels
- **Data Cleaning and Normalization**:
  - Categorical feature processing:
    * Applied one-hot encoding to the `type` feature (CASH_IN, CASH_OUT, etc.)
    * Justification: Non-ordinal nature with limited classes (5 transaction types)
  - Numerical feature transformation:
    * Standardized using `PowerTransformer` (Yeo-Johnson method)
    * Features processed: `amount`, `oldbalanceOrg`, `newbalanceOrig`, `oldbalanceDest`, `newbalanceDest`
    * Output: $\mu = 0$, $\sigma = 1$ for all numerical features
- **Class Imbalance Handling**:
  - Original distribution: 0.2% fraud (12,732 cases) vs. 99.8% legitimate
  - Applied stratified downsampling:
    * Minority-class-matched sampling (1:1 ratio)
    * Final balanced dataset: 25,464 transactions (50% fraud)
    * Preserved all fraudulent cases through sampling with replacement
- **Data Splitting**:
  - Temporal split (70/15/15) to simulate real-world deployment:
    * Training: First 70% chronologically (17,825 transactions)
    * Validation: Next 15% (3,820 transactions)
    * Test: Final 15% (3,819 transactions)
  - Stratification maintained across all splits

4.1.3 SEC Filings Dataset

- **Data Acquisition**:
  - Collected via SEC EDGAR API (2015-2023 period)
  - Balanced dataset: 85 fraudulent vs. 85 non-fraudulent companies
  - Document types: 10-K annual reports and 10-Q quarterly reports
- **Text Preprocessing**:
  - XML stripping and HTML tag removal
  - Section segmentation (MD&A, Risk Factors, Footnotes)
  - Sentence boundary detection with SpaCy's en_core_web_lg
- **Document Chunking**:
  - Challenge: Average filing length = 45,000 words (150 pages)
  - Solution: Hierarchical chunking:
    * First-level: Section-wise division (MD&A, Risks, etc.)
    * Second-level: Semantic paragraph chunks (MAX_CHUNK_LENGTH=512 tokens)
    * Overlap: 64 tokens between consecutive chunks
  - Statistics:
    * Input: 170 original filings
    * Output: 127,152 processed chunks (747 chunks/filing)
    * Mean chunk length: 498.3 tokens (=11.2)
- **Embedding Strategy**:
  - Model: Longformer (max position embeddings=4,096)

  - Processing:
    * Chunk-level embeddings generated separately
    * Attention mask for padding/truncation
  - Aggregation methods:
    * Mean pooling across all chunk embeddings
    * Section-weighted averaging (MD&A $\times 2$ weight)
    * Attention-based aggregation (learned during fine-tuning)
- **Class Balancing**:
  - Natural 1:1 ratio maintained (85 fraud/85 non-fraud)
  - Augmentation for rare fraud subtypes:
    * Synonym replacement in critical sections
    * Template-based synthetic fraud pattern insertion
- **Train-Test Split**:
  - Time-based partitioning:
    * Training: 2015-2020 filings (120 companies)
    * Validation: 2021 filings (25 companies)
    * Test: 2022-2023 filings (25 companies)
  - Stratified by fraud type (revenue recognition, asset misclassification, etc.)

4.2 Phase 2: LLM Model Selection & Fine-Tuning

- **Unified Model Architecture**:
  - Base framework: HuggingFace Transformers
  - Shared classification head:
    * Single dense layer (768D $\rightarrow$ 2D) with dropout (p=0.1)
    * Softmax activation for probability outputs
- **Dataset-Specific Adaptations**:
  - *For structured data (CreditCard/PaySim)*:
    * Textualization: Numerical features $\rightarrow$ natural language templates
    * Model: DistilBERT (optimal for short synthetic texts)
    * Max length: 128 tokens
  - *For documents (SEC Filings)*:
    * Model: Longformer (handles 4K token sequences)
    * Chunk processing with cross-attention aggregation
- **Training Protocol**:
  - Common hyperparameters:
    * Optimizer: AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.999$)
    * Base LR: 2×10^{-5} (linear decay with 10% warmup)
    * Batch size: 16 (gradient accumulation for SEC filings)
  - Imbalance mitigation:
    * Class-weighted loss: $w_{fraud} = \sqrt{N_{total}/N_{fraud}}$
    * Focal loss ($\gamma = 2.0$) for hard examples
- **Validation Strategy**:
  - Metrics:
    * Primary: AUPRC (area under precision-recall curve)
    * Secondary: F2-score (recall-weighted)
  - Early stopping:
    * Patience: 3 epochs (monitoring validation AUPRC)

    * Minimum delta: 0.005
- **Computational Setup**:
  - Hardware: NVIDIA A100 (40GB) GPUs
  - Mixed-precision training (FP16)
  - Gradient clipping (max norm=1.0)

4.2.1 Cross-Dataset Learning

The fine-tuning pipeline incorporated three key innovations:

(a) **Transfer Learning Protocol**:
- Initialized all models from FinBERT weights
- Progressive unfreezing: bottom layers → classification head

(b) **Multi-Task Formulation**:
- Shared feature extractor across datasets
- Dataset-specific adapters (LoRA layers)

(c) **Augmentation Techniques**:
- Numerical: Gaussian noise ($\sigma = 0.1$) on amount/time features
- Textual: Synonym replacement (20% probability)

4.3 Phase 3: Environment and Simulator Development

- **Unified Environment Framework**:
  - Built on OpenAI Gym API (v0.26.2)
  - Common interface for all datasets:
    * `reset()`: Loads new episode with shuffled transactions
    * `step(action)`: Processes classification decision
    * `render()`: Visualizes decision confidence scores
- **Embedding Pipeline**:
  - Precomputed features:
    * Text-based: BERT-style embeddings (768D)
    * Structured: PCA-reduced numerical features (32D)
    * Hybrid: Concatenated representations (800D)
  - Storage: HDF5 format for memory-mapped access
- **Core Environment Design**:
  - Observation Space:
    * `Box(low=-inf, high=inf, shape=(N,))` where N ∈ [32, 800]
    * Dynamic feature scaling per dataset
  - Action Space:
    * `Discrete(2)` for binary classification
    * Optional `Discrete(3)` for "review needed" action
- **Episode Dynamics**:
  - Variable episode lengths:
    * Full dataset mode (all transactions)
    * Sliding window mode (100-500 transactions)
  - Terminal conditions:
    * Exhausted transaction buffer
    * Cumulative reward threshold exceeded
    * Early fraud pattern detection

- **Simulator Features**:
  - Synthetic fraud injection:
    - Adversarial pattern generation
    - Concept drift simulation
  - Benchmarking mode:
    - Compares against rule-based systems
    - A/B testing with different reward functions

4.3.1 Cross-Dataset Compatibility

The environment automatically adapts to each dataset through:

1. **Feature Normalization**:
   - Z-score standardization per feature channel
   - Dataset-specific clipping thresholds
2. **Temporal Handling**:
   - Time-series mode for transaction datasets
   - Document-sequence mode for SEC filings
3. **Performance Metrics**:
   - Real-time calculation of precision/recall
   - Cost-sensitive accuracy tracking

4.4 Phase 4: Training the RL Agent

In this phase, we train each agent in the fraud-detection environment using consistent protocols and logging. All experiments use the Stable-Baselines3 library with GPU acceleration where available.

Dataset Split & Environment Wrapping

- **Split:** Transactions are divided into 80% training, 10% validation, and 10% test sets, stratified by class.
- **Wrapper:** We wrap the vector observations (numeric features + 768-dim text embeddings) in a custom Gym environment that returns normalized states and handles reward shaping (+1 for correct flag, –1 for missed fraud, –0.1 for false alarm).

Algorithm-Specific Training

Deep Q-Network (DQN)

- **Replay Buffer:** Capacity = 100 000 transitions; start learning after 5 000 random steps.
- **Batch Size & Updates:** 128 samples per gradient step; target network updated every 1 000 steps.
- **Exploration Schedule:** ε decayed linearly from 1.0 to 0.05 over the first 50 000 steps.
- **Training Length:** 200 000 timesteps, with model checkpoint saved every 25 000 steps.

Advantage Actor-Critic (A2C)

- **Rollout Length:** 5 steps per update; five parallel environments to decorrelate samples.

- **Batch Size & Updates:** Updates every 128 transitions, optimizing actor and critic simultaneously.
- **Entropy Coefficient:** 0.01 to encourage exploration early in training.
- **Training Length:** 100 000 timesteps, with evaluation callback every 10 000 steps.

Proximal Policy Optimization (PPO)

- **Rollout Length:** 2048 steps; four parallel environments.
- **Epochs & Minibatches:** 10 epochs per rollout, minibatch size = 64.
- **Clipping Range:** $\epsilon = 0.2$; value-function coefficient = 0.5.
- **Training Length:** 150 000 timesteps; model saved on improvement in validation reward.

Contextual Bandit

- **Algorithm:** Linear UCB with ridge regularization ($\lambda = 1$).
- **Epochs:** 100 passes over training set; no temporal dependence.
- **Reward Signal:** Immediate reward only; no future return considered.

LinUCB

- **Algorithm:** LinUCB with confidence parameter $\alpha = 1.0$.
- **Updates:** Context vector and covariance matrix updated after each transaction.
- **Training:** Single-pass over the training set.

Callbacks & Logging

- **EvaluationCallback:** Every 5 000 timesteps, evaluate on validation set and log mean reward.
- **CheckpointCallback:** Save model weights when validation reward improves.
- **TensorBoard:** Record training curves for loss, entropy, Q-values (for DQN), and reward.

Infrastructure & Reproducibility

- **Hardware:** NVIDIA GPU with CUDA support; CPU fallback if unavailable.
- **Software:** Python 3.9, Stable-Baselines3 1.8.0, PyTorch 1.12.1.
- **Random Seeds:** Fixed seeds for NumPy, PyTorch, and Gym to ensure consistent runs.

Chapter 5

Evaluation and Benchmarking

5.1 Results & Analysis

5.1.1 DQN Model

To assess the effectiveness of the trained DQN agent in classifying transactions, we conducted a comprehensive evaluation involving reward trends, Q-value analysis, and classification performance. The results are presented through both quantitative metrics and qualitative reward dynamics visualizations.

Mean Episode Reward

During training, the agent's episode reward underwent distinct phases:

Initial Rapid Increase: In the early steps, as the exploration rate (ε) decayed from its maximum, the agent began exploiting its learned Q-values. This transition enabled sharp performance gains as it started to make informed decisions.

Moderate Ascent: As training progressed, the learning rate gradually declined, leading to more conservative updates. The reward curve smoothed out, indicating policy refinement and improved stability.

These patterns suggest that the exploration and learning schedules were effective in guiding the agent from exploratory behavior to reliable decision-making.

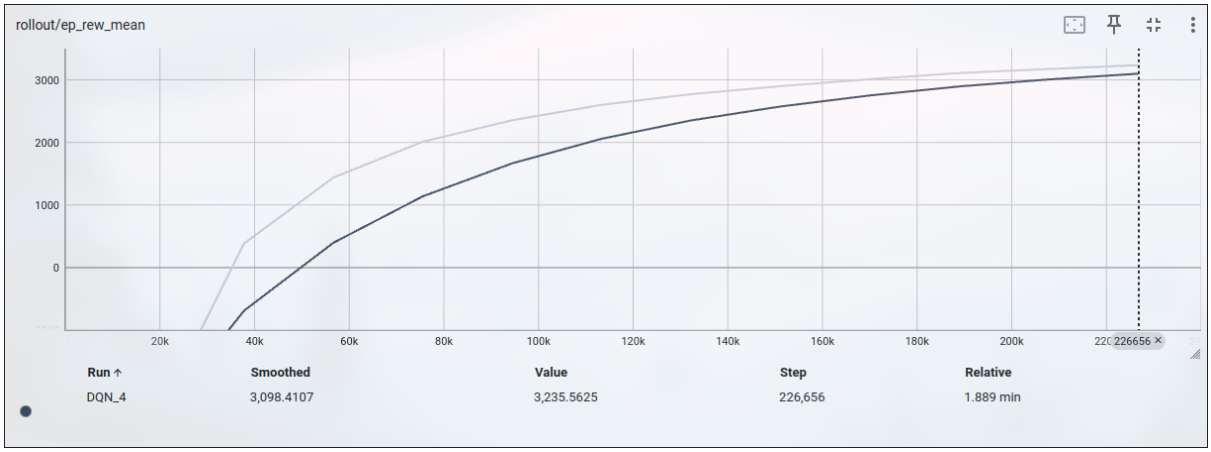

Figure 5.1: Mean reward per Episode

Training Loss Evolution

The training loss exhibited the following trends:

High Initial Loss: Training started with large temporal-difference (TD) errors due to random replay samples and an untrained Q-network. This was expected and reflected the model's initial lack of knowledge.

Stabilization and Decline: As the agent improved, the loss steadily decreased. Large batch sizes and gradient clipping helped reduce variance and contributed to stable updates.

Late-Stage Increase: Towards the end of training, the replay buffer became dominated by on-policy transitions as ε approached its minimum. This reduced sample diver-

sity and caused the TD error to slightly rise again, suggesting that early stopping could be beneficial to halt training before overfitting to these transitions.

Figure 5.2: Training Loss

Evaluation Reward Analysis

Evaluation was conducted using a fixed environment to measure the agent's learned policy in terms of reward acquisition. Figure 5.3 summarizes this with two key plots.

Step-Wise Rewards (Left Panel):

- **Positive Rewards:** Frequent and consistent, these suggest successful actions such as correctly identifying fraud or non-fraud.
- **Negative Rewards:** Less frequent but impactful, these likely reflect misclassifications—either false positives or false negatives.
- **Zero Rewards:** Representing neutral outcomes, these may indicate uncertain or ambiguous transaction decisions.

Cumulative Rewards (Right Panel): The cumulative reward increased steadily throughout the evaluation episode, surpassing 1000 by step 600. This upward trend implies that the agent's policy led to consistent positive outcomes, reinforcing the effectiveness of the learned decision strategy.

Average Q-Values Per Action

Figure 5.4 presents the average Q-values associated with each action during evaluation.

- Both actions exhibited similarly high average Q-values, indicating high confidence in decision-making regardless of the chosen label.
- This balance implies that the agent has learned effective strategies for both detecting fraud and correctly identifying legitimate transactions.
- The model does not favor one action over the other, a sign of robustness and fairness in decision-making across classes.

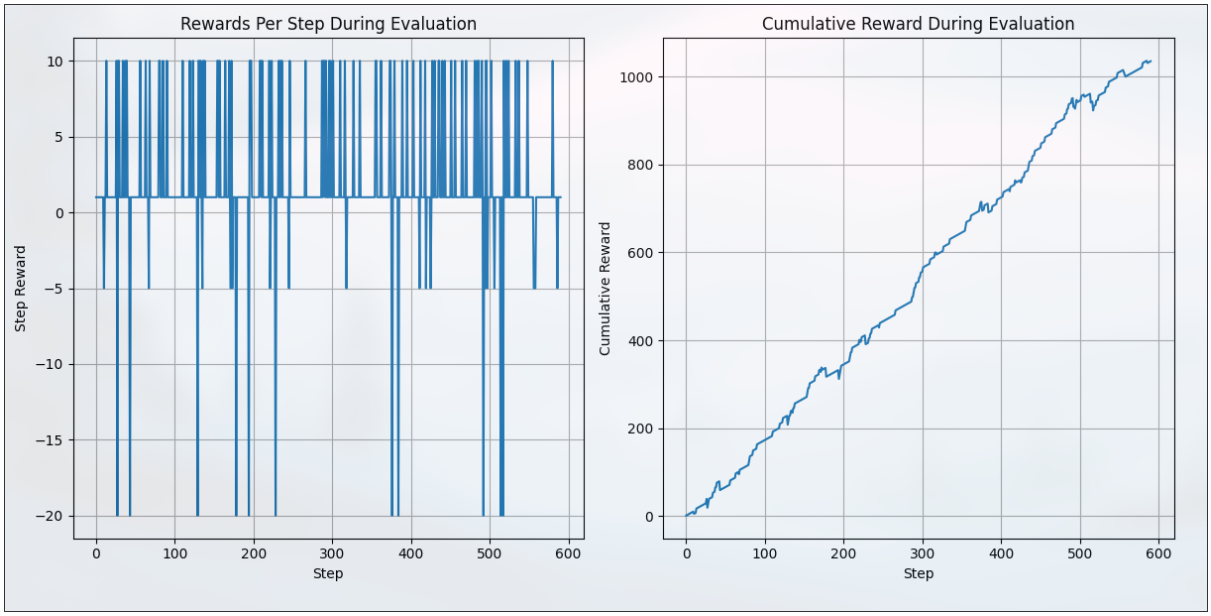

Figure 5.3: Reward Dynamics During Evaluation. Left: Step-wise rewards. Right: Cumulative reward trajectory.

Classification Performance Metrics

To quantify the classification ability of the trained agent, we computed standard metrics from its confusion matrix, shown in Figure 5.5.

- **Accuracy:** 95.09% – The agent achieved high correctness across all transactions.
- **Precision (Fraud):** 82.86% – Of predicted frauds, the majority were truly fraudulent.
- **Recall (Fraud):** 88.78% – The agent identified most actual fraudulent transactions.
- **F1 Score (Fraud):** 85.71% – A strong balance between avoiding false alarms and detecting real frauds.

The confusion matrix reflects high effectiveness in both fraud detection (true positives) and minimizing false positives, underscoring the agent's practical utility.

5.1.2 A2C Model

To evaluate the A2C agent's behavior and classification capabilities, we analyzed policy dynamics, cumulative reward trends, and classification outcomes during evaluation episodes. The following subsections detail the agent's performance.

Policy Loss Curve

The policy loss trajectory during training reveals significant insights into the learning dynamics.

- **Oscillatory Pattern:** Sharp spikes and drops occur roughly every 20,000 steps. These likely align with environment resets or model checkpoint events.

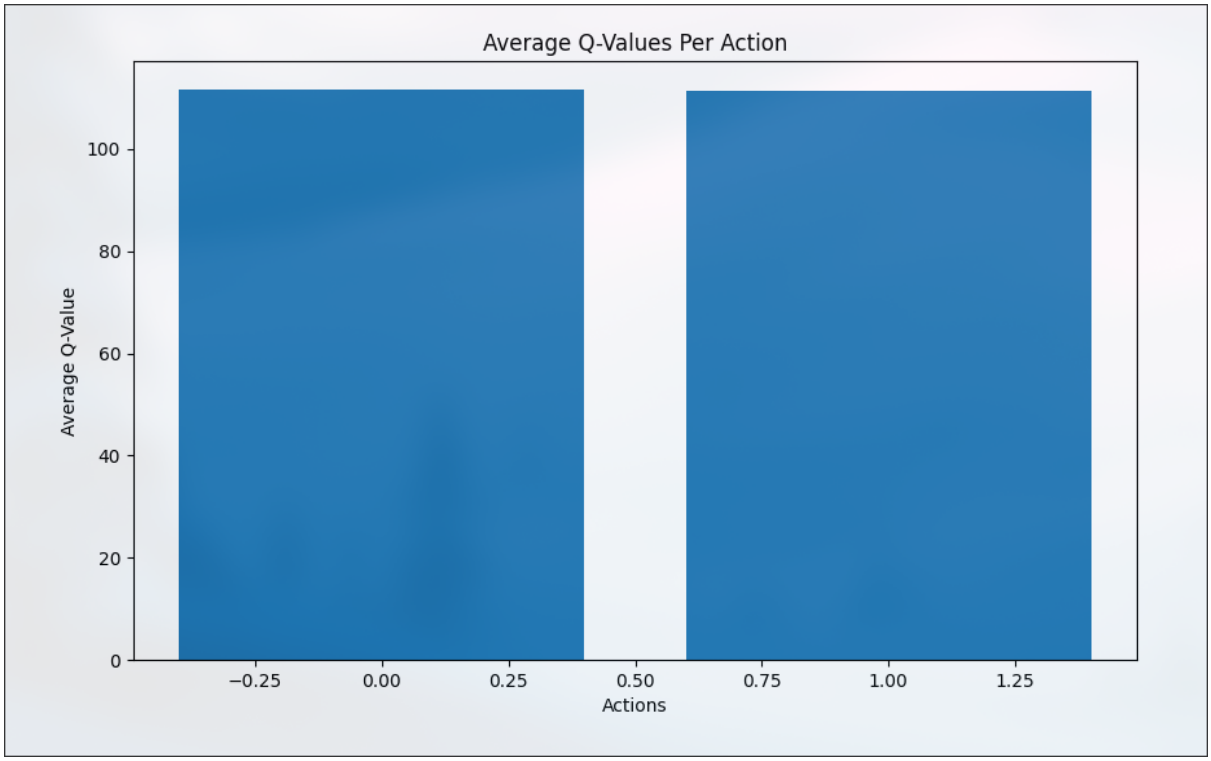

Figure 5.4: Average Q-Values for Actions 0 (non-fraud) and 1 (fraud) during evaluation.

- **Stabilization Phase:** After approximately 120,000 steps, the oscillations dampen, and the loss consistently hovers near zero.
- **Final Value:** At the end of training (step 236,000), the smoothed loss reaches approximately -0.035, indicating small corrective updates and a nearly deterministic policy.

Action Probabilities and Policy Entropy

Action Probabilities:

- The action probabilities are almost binary—typically at 0 or 1—across all 600 evaluation steps.
- This indicates a confident and nearly deterministic policy. Dense clusters of "Fraud" actions suggest strong signal detection in embedded state representations.

Policy Entropy:

- Entropy is effectively zero across most of the evaluation.
- Occasional spikes (up to 0.7) appear in ambiguous states, where the agent temporarily reconsiders less certain actions.
- These entropy spikes reveal moments of uncertainty, but the general trend confirms confident decision-making.

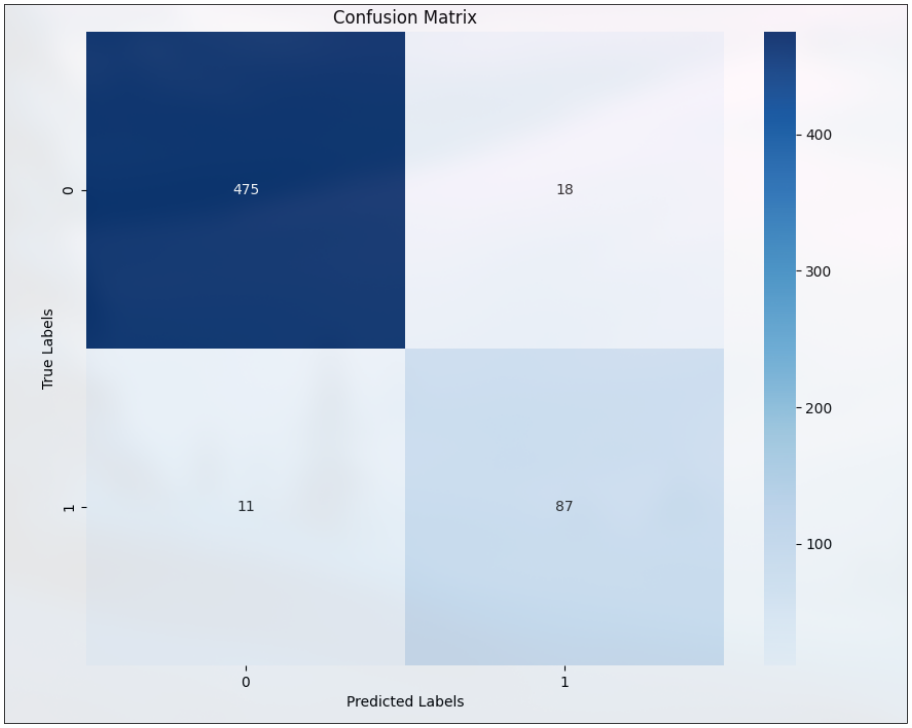

Figure 5.5: Confusion Matrix of DQN Model on Test Set.

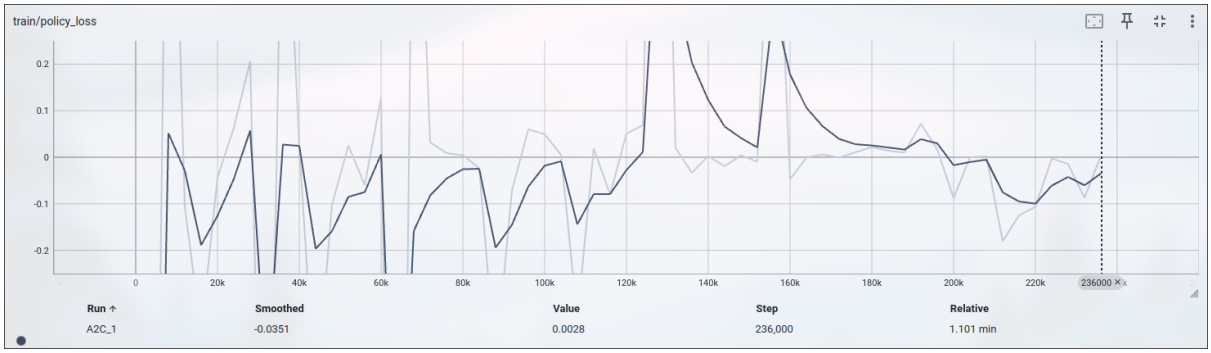

Figure 5.6: Policy Loss Curve for A2C Agent during Training

4. Confusion Matrix

- **True Negatives (463):** 93.9% of legitimate transactions correctly classified.
- **True Positives (88):** 89.8% of fraudulent transactions accurately detected.
- **False Positives (30):** 6.1% of legitimate transactions incorrectly flagged as fraud.
- **False Negatives (10):** 10.2% of fraudulent transactions missed.

5. Classification Metrics Summary

- **Accuracy:** 93.23%
- **Precision (Fraud):** 74.58%
- **Recall (Fraud):** 89.80%

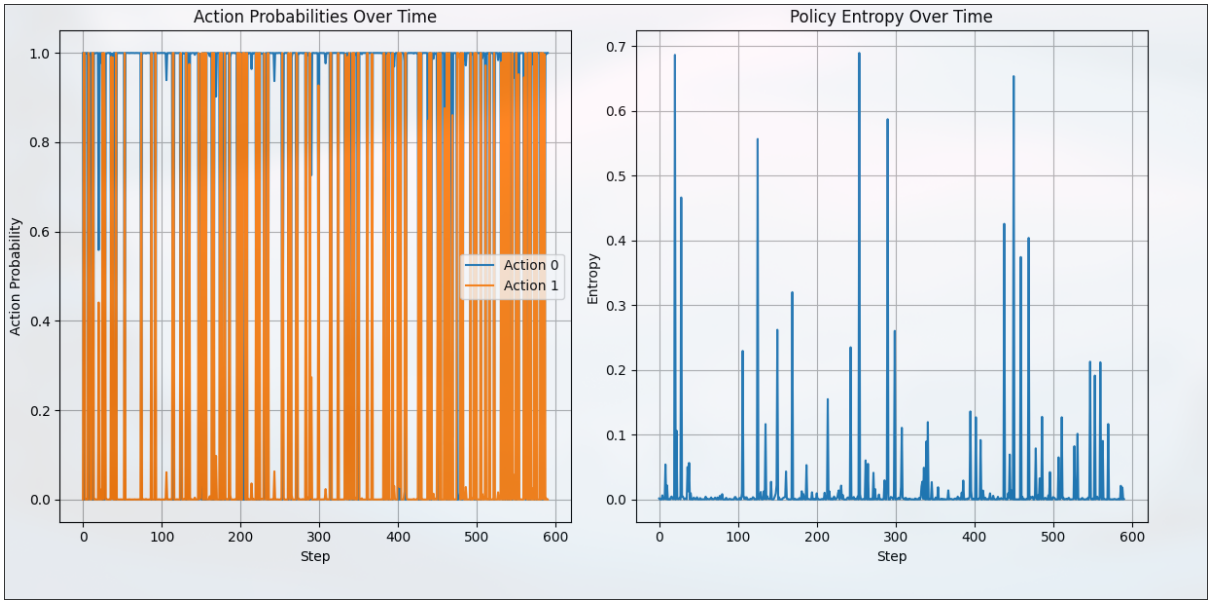

Figure 5.7: A2C Agent Evaluation: Action Probabilities and Policy Entropy

- **F1 Score (Fraud):** 81.48%
- **Average Reward per Step:** ∼1.68

Interpretation

The A2C agent successfully learns a high-recall policy capable of detecting nearly 90% of fraudulent transactions, at the cost of a moderate false-positive rate. Its nearly deterministic action probabilities and low entropy reflect strong confidence in its decisions. The cumulative reward trajectory further reinforces the model's robustness, showcasing a stable and effective policy under the fraud detection reward design.

5.2 Baseline Comparisons

For the PaySim dataset we compare five approaches: two policy-gradient RL methods (A2C, PPO), a value-based RL method (DQN), and two contextual bandits (naïve and linear).

Model	Accuracy	Precision_1	Recall_1	$\text{F}_{1,1}$	Macro F_1
A2C	0.9992	1.0000	0.9970	0.9985	0.9990
PPO	0.9695	0.8936	0.9967	0.9424	0.9608
DQN	0.8913	1.0000	0.5646	0.7217	0.8271
Contextual Bandit	0.6400	0.2600	0.2300	0.2400	0.5000
LinUCB	0.5285	0.2838	0.5829	0.3817	0.5003

Table 5.1: Validation/test performance on the PaySim fraud detection task (class 1 = fraud).

Model Analysis

A2C (Best Model) Achieves near-perfect precision and recall on both classes. The on-policy actor–critic framework benefits from low-variance advantage estimates and fre-

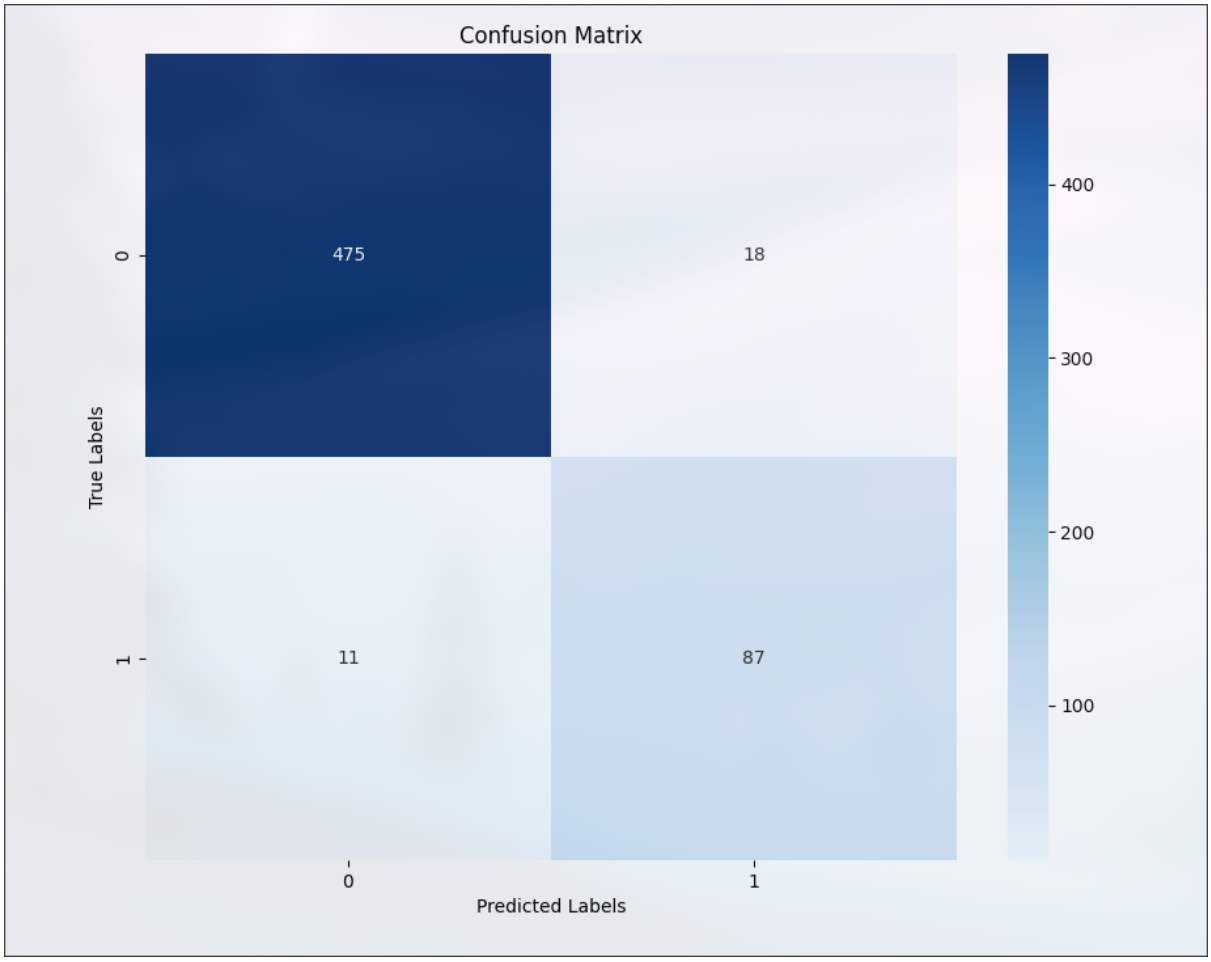

Figure 5.8: Confusion Matrix of A2C Model on Test Set

quent policy updates, which is especially helpful under our heavily imbalanced reward structure (TP=+1, TN=0, FP=−1, FN=−5). By directly optimizing the expected return with GAE, A2C learns to prioritize avoiding costly false negatives while still capturing the majority class with high fidelity.

PPO (Policy-Gradient) Strong performance (accuracy $\approx$ 97%) but slightly lower than A2C. PPO's clipped surrogate objective trades off exploration and stability; here it occasionally undercalls fraud (precision = 0.8936) to maintain stable updates, despite its very high recall (0.9967). PPO is robust and comparatively easy to tune, though in extreme class-imbalance settings it may favor safe predictions unless hyperparameters (clip range, learning rate) are carefully calibrated.

DQN (Value-Based Q-Learning) Solid precision on fraud (1.000) but poor recall (0.5646), yielding many false negatives. As a value-based method, DQN struggles with sample efficiency in high-dimensional embedding spaces, and its ε-greedy exploration can miss rare fraud instances. With more training iterations and a larger replay buffer, recall could improve, but DQN will likely remain less stable than policy-gradient methods on this cost-sensitive task.

Contextual Bandit Very low recall on fraud (0.23) despite moderate precision. Treating each decision independently (no state feedback) makes it impossible to learn long-term patterns in sequential embeddings. It performs only marginally better than random on the minority class and cannot leverage structure in the embedding space beyond immediate reward estimates.

LinUCB (Linear Contextual Bandit) Baseline linear model with moderate recall (0.58) but low precision (0.28) and overall accuracy barely above chance (0.53). Its simplicity (linear reward model plus uncertainty bonus) fails to capture the nonlinear relationships embedded by the fine-tuned LLM. It serves as a useful baseline to demonstrate that naive bandit approaches are insufficient for high-dimensional, cost-sensitive fraud detection.

Limitations & Considerations

- **Sample Efficiency & Compute:** RL methods (DQN, A2C, PPO) require thousands of episodes, which can become computationally expensive when working with large embedding vectors.
- **Reward Shaping:** Heavily penalizing false negatives (FN$=-5$) biases policies toward over-alerting; fine-tuning these weights is nontrivial and may introduce excessive false positives.
- **Overfitting Risk:** On-policy methods (A2C, PPO) can overfit to the validation distribution without careful regularization or early stopping.
- **Stability vs. Expressivity:** Value-based methods (DQN) can be unstable in high dimensions; policy-gradient methods trade variance for bias via clipping and advantage estimates.

The Value of Combining LLMs & RL Agents

- **Rich Representations:** Fine-tuned LLM embeddings capture textual and contextual cues from financial transactions that shallow or linear models miss.
- **Cost-Sensitive Decision Making:** RL naturally incorporates non-differentiable objectives (e.g., imbalanced misclassification costs) directly into the learning signal.
- **Sequential Context:** Modeling fraud detection as a sequential decision process allows RL to leverage patterns across related transactions or time-ordered events.
- **Adaptivity:** An RL policy can continually adapt to emerging fraud patterns via online learning, whereas static classifiers require costly retraining.

Chapter 6

Challenges, Pitfalls and Resources

6.1 Key Challenges and Mitigation

Fraud detection with LLM+RL poses several overarching challenges:

- **Extreme Class Imbalance:** Positive (fraud) cases are rare (e.g. 0.17% in Credit Card). Mitigation: cost-sensitive reward shaping, stratified sampling, GAN-based oversampling, and monitoring AUPRC rather than accuracy.
- **Overfitting & Generalization:** High model capacity (LLM + deep RL) risks memorizing training fraud patterns. Mitigation: regularization (weight decay, dropout), early stopping via validation reward, and cross-validation on held-out temporal splits.
- **RL Stability & Sparsity:** Sparse fraud rewards can destabilize off-policy learners (e.g. DQN) and lead to catastrophic forgetting. Mitigation: reward shaping (intermediate penalties), prioritized experience replay, entropy regularization, and evaluation callbacks to detect divergence early.
- **Explainability:** Combined LLM embeddings and RL policies are opaque to analysts. Mitigation: logging LLM attention weights, using post-hoc explainer methods (SHAP/LIME) on embedding+policy inputs, and storing rationale texts from the LLM.

6.1.1 Datasets Considerations

Each dataset brings unique preprocessing and resource challenges:

Credit Card (IEEE-CIS) The dataset contains transactions made by credit cards in September 2013 by European cardholders. This dataset presents transactions that occurred over a two-day period, where we have 492 frauds out of 284,807 total transactions. The dataset is highly unbalanced: the positive class (frauds) accounts for only 0.172% of all transactions.

It contains only numerical input variables, which are the result of a PCA transformation. Unfortunately, due to confidentiality issues, the original features and more background information about the data cannot be provided. Features `V1, V2, ..., V28` are the principal components obtained with PCA. The only features that have not been transformed are `Time` and `Amount`.

PaySim Mobile Transactions Synthetic, categorical and numeric fields with injected fraud scenarios. Simulator fidelity may not transfer to real-world distributions—requires careful domain adaptation and stress-testing.

SEC Filings (MD&A Texts)

- **Huge Document Size:** Average 1.28M characters per report, exceeding typical LLM context windows (2K–32K tokens).
- **Chunking Pipeline:** We segmented each filing into overlapping chunks (e.g. 2 048-token windows with 50% stride) to preserve continuity. This adds complexity in data loaders and increases storage for intermediate text files.
- **Encoding Complexity:** Each chunk must be tokenized and embedded separately, then aggregated (e.g. mean, attention-based pooling) to form a single state vector. Designing an efficient batching strategy and aggregator is non-trivial.

- **Compute Resources:** Fine-tuning LLMs on these chunks demands large GPU memory (¿16 GB), multi-GPU parallelism or model-parallel frameworks, mixed-precision, and gradient checkpointing to avoid OOM. End-to-end backprop through both LLM and RL agent further multiplies resource requirements.
- **Limitations:** Chunk-level processing loses global document context; embedding aggregation may dilute local signals. High preprocessing and inference latency hinders real-time deployment.

6.2 Additional Resources

For reproducibility and further development, we recommend:

- **Transformers & Tokenizers:** HuggingFace Transformers, Datasets, Tokenizers, and Accelerate for LLM fine-tuning and chunk management.
- **Reinforcement Learning:** Stable-Baselines3, RLlib; evaluation callbacks and integration examples in their documentation.
- **Explainability Tools:** SHAP, LIME for post-hoc analysis of embeddings and policy inputs.
- **Similarity Search:** FAISS for efficient retrieval of relevant chunks during inference.
- **Key Papers & Repos:**
  - Dang et al. (2021) "Reinforcement Learning for Fraud Detection"
  - Purva Singh et al. Gym-based DQN implementation (GitHub)
  - Zhao et al. (2023) GPT-based payment fraud model
- **Compute Platforms:** AWS p3/p4 instances, GCP TPU v3, or on-prem NVIDIA DGX for large-scale LLM+RL training.

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