Decentralized Credit Scoring for Compound V2 Wallets

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1. Introduction

The goal of this project is to develop a decentralized, behavior-based credit-scoring system for Ethereum wallets using Compound V2 transaction data. By analyzing on-chain actions—deposits, borrows, repayments, withdrawals, and liquidations—we generate a continuous score from 0 to 100 that reflects each wallet's reliability and risk profile. High scores denote prudent, consistent usage; low scores flag risky or exploitative patterns.

2. Criteria for Good vs Bad Wallet Behaviour

Good behaviour is characterized by high repay activity, sustained protocol engagement, diverse asset interaction, and low liquidation risk. Bad behaviour includes frequent liquidations, poor repayment patterns, and low transaction diversity or abrupt, bot-like usage. Wallets that contribute large volumes of capital and show consistent repayment patterns are favoured.

3. Data Selection and Processing

3.1 Raw Data Sources

Three largest chunks of the Compound V2 Ethereum transaction log were used:

1. compoundV2_transactions_ethereum_chunk_0.json
2. compoundV2_transactions_ethereum_chunk_1.json
3. compoundV2_transactions_ethereum_chunk_2.json

3.2 Flattening & Cleaning

- **Flatten:** All JSON lists concatenated into one DataFrame, tagging each row with its action.
- **Rename & Types:** Renamed account.id → wallet_id, asset.symbol → asset_symbol, converted epoch timestamp to datetime, and cast amountUSD to float.
- **Filter Core Actions:** Retained only the five actions most relevant—deposits, borrows, repays, withdraws, liquidates—and dropped any records missing key fields.
- **Persistence:** Saved intermediate tables as Parquet (transactions.parquet, transactions_clean.parquet) for reproducibility.

3. Feature Engineering

Key features were engineered from raw logs:

- txn_count: Total transaction actions
- total_usd: Total dollar value transacted
- repays, borrows, liquidates: Action-specific counts
- txns_per_day: Activity rate over time
- borrow_to_repay: Proxy for repayment behavior
- liq_rate: Liquidation to transaction ratio
- avg_txn_value_usd: Engagement scale
- unique_assets: Token diversity

These were aggregated at the wallet level to represent behavioral patterns.

4. Modelling Approach

We adopted an unsupervised machine learning approach using KMeans clustering (k=4). Wallets were grouped based on transactional bbehaviours and patterns. Each cluster was then scored according to average rule-based scores,capturing their risk tier. This ML-based score was blended with a rule-based percentile score to create a final,interpretable credit score.

4. Scoring Methodology

- **Rule-Based Component (60%):**
  A percentile-based score was calculated using:
  - `txn_count` (engagement)
  - `total_usd` (capital contribution)
  - `repays` (responsibility)
  - `liquidates` (risk indicator)

  Weights:
  - Activity Score = 70%
  - Safety Score = 30%

  Final rule-based score was rescaled to [0–100].

- **ML-Based Component**:
  Wallets were clustered using KMeans (k=4) based on normalized behavioural features:
  - Transaction volume

- Repay/borrow balance
- Liquidation ratio
- Daily engagement
- Asset diversity

Clusters were then ranked based on their average rule-based score and mapped to a score tier.

- **Blended Final Score**:
  final_score = 0.6 * rule_based_score + 0.4 * ml_score
  This provides both interpretability and AI-driven clustering.

5. Results

- **Range:** Final scores span the full 0–100 range with median ≈65.
- **Top-1,000 Export:** Highest-scoring wallets saved to outputs/top_1000_wallet_scores.csv.
- **Spot Checks:**
  High scorers show high activity & zero liquidations.
  Low scorers have one or more liquidations and lower activity.

6. Limitations & Future Work

- **Limitations:**
  - No ground-truth risk labels prevent supervised training.
  - Infrequent users may be misclassified due to limited history.

- **Future Work:**
  - Integrate anomaly detection (e.g., Isolation Forest)
  - Use LSTM or time-series prediction for longitudinal wallet behaviour
  - Incorporate token volatility or market context into scoring

7. Conclusion

This approach balances interpretability with data-driven modelling. By leveraging both engineered features and unsupervised learning, we created a resilient credit scoring mechanism for decentralized finance participants. The methodology ensures that scores reflect not just transaction volume but also behavioural quality and systemic risk contribution.