Methodology Document: Compound V2 Wallet Credit Scoring

Project: AI-Powered Decentralized Credit Scoring (Zeru Finance)
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1. Overview and Objective

- **Objective:** To develop a credit scoring system that assigns a score between 0 and 100 to Compound V2 wallets based solely on their historical on-chain transaction behavior. Higher scores indicate reliable and responsible protocol usage, while lower scores reflect risky, bot-like, or potentially exploitative behavior.
- **Approach:** An unsupervised, feature-engineering-driven approach was adopted due to the absence of predefined labels. The methodology involves data processing, extensive feature engineering, outlier treatment (ratio capping), feature scaling, and a weighted rule-based scoring mechanism to derive the final credit scores.

2. Data Source and Preprocessing

- **Dataset:** Raw, transaction-level JSON data from the Compound V2 protocol, encompassing actions such as deposits, borrows, repays, withdraws, and liquidations.
- **Data Loading:** The three largest transaction data files (`compoundV2_transactions_ethereum_chunk_0.json`, `compoundV2_transactions_ethereum_chunk_1.json`, `compoundV2_transactions_ethereum_chunk_2.json`) were loaded.
- **Initial Processing & Consolidation:**
    - Transactions were parsed from JSON.
    - Data for `deposits`, `withdraws`, `borrows`, `repays`, `liquidates` across all files were consolidated into respective Pandas DataFrames.
    - Nested JSON fields were flattened.
    - Data types were converted (`amount`/`amountUSD` to numeric, `timestamp` to datetime).
    - A `transaction_type` column was added.
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- **Unified Transaction Log:** `common_transactions_df` was created by concatenating deposits, withdraws, borrows, and repays. `df_liquidates` was handled separately.

3. Feature Engineering

Wallet-level behavioral features were derived:

- **I. Wallet Activity & Profile:**
    - `total_transactions`, `wallet_age_days`, `active_days`, `avg_txns_per_active_day`, `distinct_assets_used_count`.
    - `days_since_last_activity`, `days_since_last_deposit`, `days_since_last_withdraw`, `days_since_last_borrow`, `days_since_last_repay`.
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- **II. Transaction-Specific Aggregations:**
    - `[action]_count`, `total_[action]_usd`, `avg_[action]_usd`, `max_[action]_usd`, `min_[action]_usd` (non-zero).
    - `distinct_assets_[action]ed_count`.
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- **III. Derived Ratios & Net Values:**
    - `net_deposit_usd`, `net_borrow_activity_usd`.
    - `repay_to_borrow_ratio_usd`, `borrow_to_deposit_ratio_usd`, `withdraw_to_deposit_ratio_usd`.
    - *Division by zero was handled by replacing inf/-inf with 0, then filling NaNs with 0.*
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- **IV. Liquidation Behavior:**
    - `times_liquidates_count` (as Liquidatee).
    - `total_usd_liquidated_as_liquidatee`.
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- **V. Behavioral Indicators:**
    - `borrow_while_having_deposits_flag`.
    - `small_usd_txns_count` (<$10 USD).
    - `percentage_small_usd_txns`.

4. Data Treatment for Modeling

- **Missing Values:** Post-aggregation NaNs in numeric features were generally filled with 0. "Days since" features for non-occurring actions were filled with the dataset's maximum observed age.

- **Ratio Capping (Outlier Treatment):** Ratios (`repay_to_borrow_ratio_usd`, `borrow_to_deposit_ratio_usd`, `withdraw_to_deposit_ratio_usd`) in the unscaled numeric feature set (`wallet_features_numeric`) were capped at their 1st and 99th percentiles to mitigate extreme outlier impact. For instance, `repay_to_borrow_ratio_usd` was capped between 0.0000 and 1.0563. This resulted in the `wallet_features_numeric_capped` DataFrame.
- **Feature Scaling:** All features in `wallet_features_numeric_capped` were standardized using `sklearn.preprocessing.StandardScaler` (fitted as `scaler_refined`), creating `wallet_features_scaled_df_refined`.

5. Credit Scoring Logic (Weighted Rule-Based System)

A weighted rule-based system was implemented:

- **Raw Score Calculation:**
  - Selected features from `wallet_features_scaled_df_refined` were assigned weights based on their expected impact on creditworthiness.
  - The `raw_credit_score` was the sum of (scaled feature value * weight).

The final weights used were:

```
feature_weights = {
    'wallet_age_days': 1.0,
    'active_days': 0.5,
    'total_deposit_usd': 0.5,
    'net_deposit_usd': 1.0,
    'repay_to_borrow_ratio_usd': 2.0,
    'borrow_to_deposit_ratio_usd': -1.5,
    'times_liquidates_count': -2.5,
    'total_usd_liquidated_as_liquidatee': -1.0,
    'net_borrow_activity_usd': -1.0,
    'percentage_small_usd_txns': -0.5,
    'days_since_last_activity': -0.75,
    'distinct_assets_used_count': 0.25,
    'total_transactions': 0.25,
    'days_since_last_deposit': -0.2,
    'days_since_last_withdraw': -0.1,
    'days_since_last_borrow': -0.3,
    'days_since_last_repay': 0.4

}
```

- **Final Score Scaling (0-100):**
  - The `raw_credit_score` values were scaled to 0-100 using `sklearn.preprocessing.MinMaxScaler` (fitted as `score_scaler` on the distribution of raw scores from the entire dataset).
  - The final `credit_score` (float) was then rounded to the nearest whole number for the CSV output.

6. Initial Exploration (K-Means Clustering)

- Unsupervised K-Means clustering (K=3 chosen via Elbow and Silhouette methods on initially scaled features) was performed for exploratory analysis. This identified behavioral segments (e.g., a very large cluster of low-activity/potentially higher-risk profiles, a moderate-sized cluster of active/leveraged users, and a tiny cluster of very high-volume "whale" users with mixed risk signals). These insights informed the understanding of feature behaviors, although the final scoring relies on the more granular weighted rule-based system.

7. Model Output and Interpretation

- The system outputs a credit score between 0 and 100 for each wallet.
- Analysis of the final score distribution (using the weights specified in section 5 and after ratio capping) revealed:
  - **Mean Score:** ~58.05
  - **Standard Deviation:** ~1.41
  - **Min Score:** 0
  - **Max Score:** 100
  - **25th Percentile:** ~57.52
  - **50th Percentile (Median):** ~58.03
  - **75th Percentile:** ~58.42

- This distribution indicates that while the scores span the full 0-100 range (with the most extreme risk profiles correctly identified at the tails), the majority of wallets (~50%) are tightly clustered in a narrow band around the mean (approx. 57.5 - 58.4). This suggests that, according to the defined features and linear weighting scheme, a large portion of the observed wallets exhibit a broadly similar, moderately risky or neutral behavioral profile within the dataset.

8. Conclusion & Rationale

This methodology provides a custom, transparent, and data-driven approach to credit scoring based on Compound V2 transaction history. The feature engineering captures diverse behavioral aspects, the ratio capping handles extreme outliers, and the weighted rule-based system allows for interpretable scores that align with predefined criteria for responsible and risky behavior. The resulting score distribution, with clearly defined tails and a dense middle, reflects the differentiated risk profiles within the analyzed dataset.