Methodology Document

Title: Credit Scoring System for Compound V2 Wallets
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1. How I Defined Good vs. Bad Wallets

To build the credit scoring system, I first needed a way to decide which wallets are considered *good* (responsible users) and which are *bad* (risky or bot-like users). Since there were no labels given, I used basic logic and behavior patterns to set this rule.

A wallet is considered **good** if:

- It has made more than 3 transactions.
- It has deposited more than $10 worth in total.

A wallet is considered **bad** if it has fewer transactions or has interacted with a very low amount of funds. This usually indicates spammy, bot-like, or unreliable behavior.

This simple rule helped me create a label for each wallet:

- 1 = Good
- 0 = Bad

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2. Feature Engineering – What I Extracted from the Data

I worked with raw transaction data that included fields like timestamp, account, asset, and amountUSD. I cleaned the data and then grouped the transactions by each wallet to get summary-level features.

Here are the wallet-level features I used:

- **Total USD value** transacted by the wallet

- **Average USD amount** per transaction
- **Standard deviation** of amounts (shows consistency or variation)
- **Number of transactions** (how active the wallet is)
- **Maximum transaction amount**
- **Active days** (difference between the first and last transaction)
- **Number of unique assets** used (diversity of usage)

These features give a complete picture of how a wallet behaves over time.

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3. Modeling Approach

Once I had the features and labels ready, I used a machine learning model to learn patterns between them. I used **XGBoost**, a popular and powerful tree-based model that works well for structured data like this.

To make sure the results were reliable and not random, I used **StratifiedKFold cross-validation**, which splits the data into multiple folds while keeping the balance between good and bad wallets. This helps the model generalize better.

After training, I used **SHAP (SHapley Additive exPlanations)** to understand why the model gave certain scores. SHAP shows which features influenced each prediction, making the system more transparent and explainable.

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4. Credit Score Conversion

The model gives a probability between 0 and 1. This tells how likely a wallet is to be "good" based on its behavior.

To turn this into a credit score, I simply multiplied the probability by 100.
For example:

- A probability of 0.9987 becomes a score of **99.87**
- A probability of 0.1245 becomes a score of **12.45**

This makes the score more human-readable and interpretable — higher scores are better.

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5. Output

The final output is a list of the **top 1,000 wallets** ranked by credit score in descending order. Each row has:

- The wallet’s account ID
- The credit score (between 0 and 100, rounded to two decimals)

This output can be used for further analysis, filtering, or insights into wallet behavior on the Compound V2 protocol.