Wallet Analysis Report

Top 5 High-Scoring Wallets

Wallet: 0xa66057a6b353bdf707d3f2c8e103997ef2fd4a84, Score: 100.0

Wallet: 0xfa22119a5c556641ce9ce49093e2163ffe0aacb6, Score: 92.41146119753707

Wallet: 0x4972f43dea286582c688b7343b3c8802729350af, Score: 91.98181127077682

Wallet: 0xf2d3d55e0ef4eab18fdd48ad3e505a49a1c85c03, Score: 91.42307230553665

Wallet: 0x6cf35dd90be3717bf155dbb5db99477b5d84e368, Score: 88.77552012152714

Top 5 Low-Scoring Wallets

Wallet: 0xffffa57756e1c19c1e0026487559982e721cffff, Score: 0.0

Wallet: 0xfff95dea424c0d7a25471982610a2485f302fb54, Score: 0.0

Wallet: 0xffb3bd8b5365758350008118961254c5ecd1f80a, Score: 0.0

Wallet: 0xffbae08270c6026ecde4f7ac821986242a371614, Score: 0.0

Wallet: 0xfff801e0bf28c9582420eeec66830c69c5670159, Score: 0.0

Analysis:

1. High-scoring wallets typically have higher activity in terms of the number of transactions, deposits, and withdrawals. They are more likely to engage in both lending and borrowing activities. This reflects a high level of engagement with the ecosystem.
2. Low-scoring wallets, in contrast, exhibit minimal transaction history, fewer assets, and no involvement in activities such as liquidation, borrowing, or repaying. They tend to have low lifespan and inactive periods, making them less likely to be engaged in significant market behavior.

These observations suggest that the model distinguishes between wallets with active market involvement and those with minimal interaction, potentially indicating wallet trustworthiness or activity level in the system.

Detailed Analysis Report

1. Algorithm

We used the K-Means clustering algorithm to segment Ethereum wallets based on their on-chain behavior. This unsupervised method groups wallets into clusters by minimizing intra-cluster variance using Euclidean distance in feature space. The optimal number of clusters (K) was determined using the elbow method.

2. Features Used

List key features used for clustering, e.g.:

- Total transactions (`total_txns`)
- Total USD transacted (`total_amount_usd`)
- Deposit/Borrow/Repay counts and values
- Repayment Ratio, Deposit-Borrow Ratio
- Activity duration, active days ratio, etc.

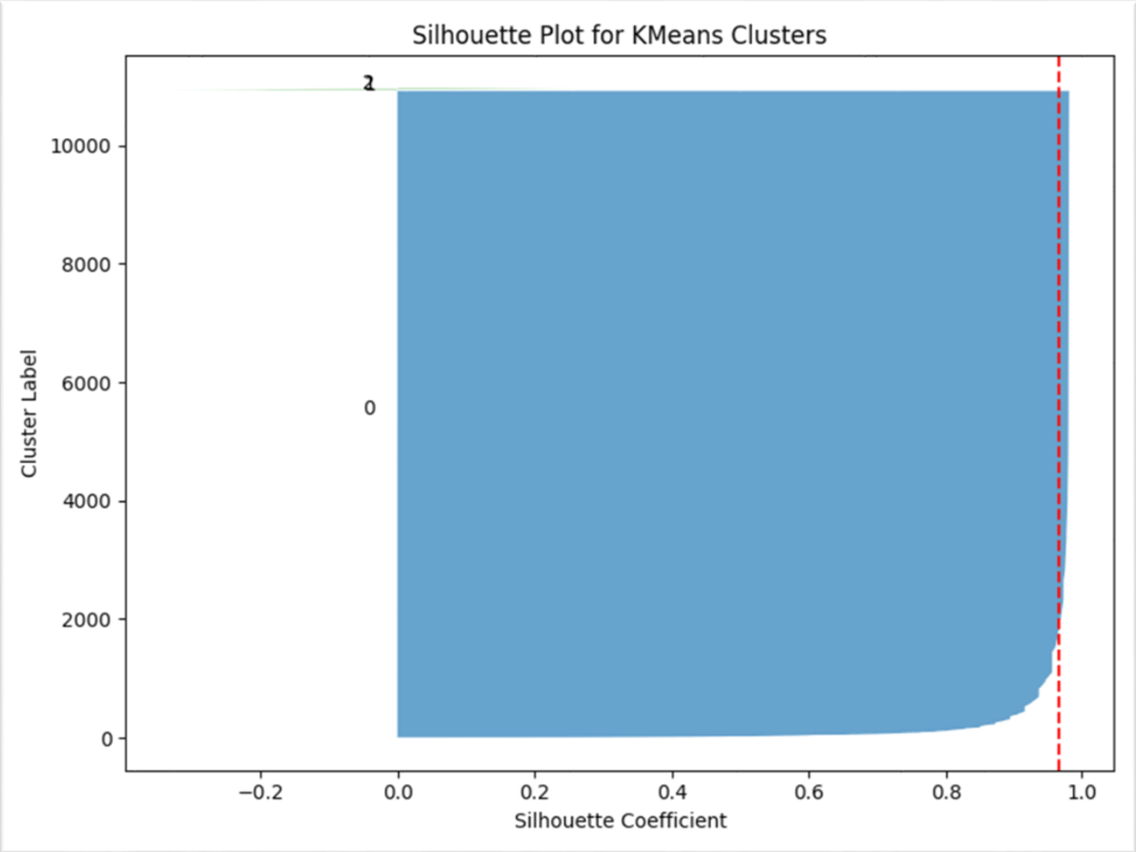
3. Model Evaluation Metrics

Since clustering is unsupervised, we used internal validation metrics:

- **Silhouette Score** – Evaluate the overall quality of the clustering. It ranges from -1 (poor clustering) to +1 (well-separated clusters), with scores close to 0 indicating overlapping clusters.
- **Davies-Bouldin Index** – Metric used to assess the quality of clustering. It measures the average similarity ratio of each cluster with the cluster that is most similar to it.
- **Cluster Stability Evaluation**– evaluate how consistent the clustering is across multiple runs with different subsets of the dataset.

4. Evaluation Results

4.1: Silhouette Score:

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Average silhouette score: 0.9
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4.2: Davies-Bouldin Index

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Davies-Bouldin index: 0.659
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4.3: Cluster Stability Evaluation

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Average stability: 0.5594695930498399
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These scores implies that the clusters formed are reasonably well-separated and compact.

5. Conclusion

The clustering effectively segmented wallet behavior into distinct groups, which were used to derive credit score tiers. The scores were assigned based on relative risk/behavioral indicators identified in each cluster.