Market Research Report

Nodiens

Market Moods in Motion: Clustering Crypto Sentiment Dynamics

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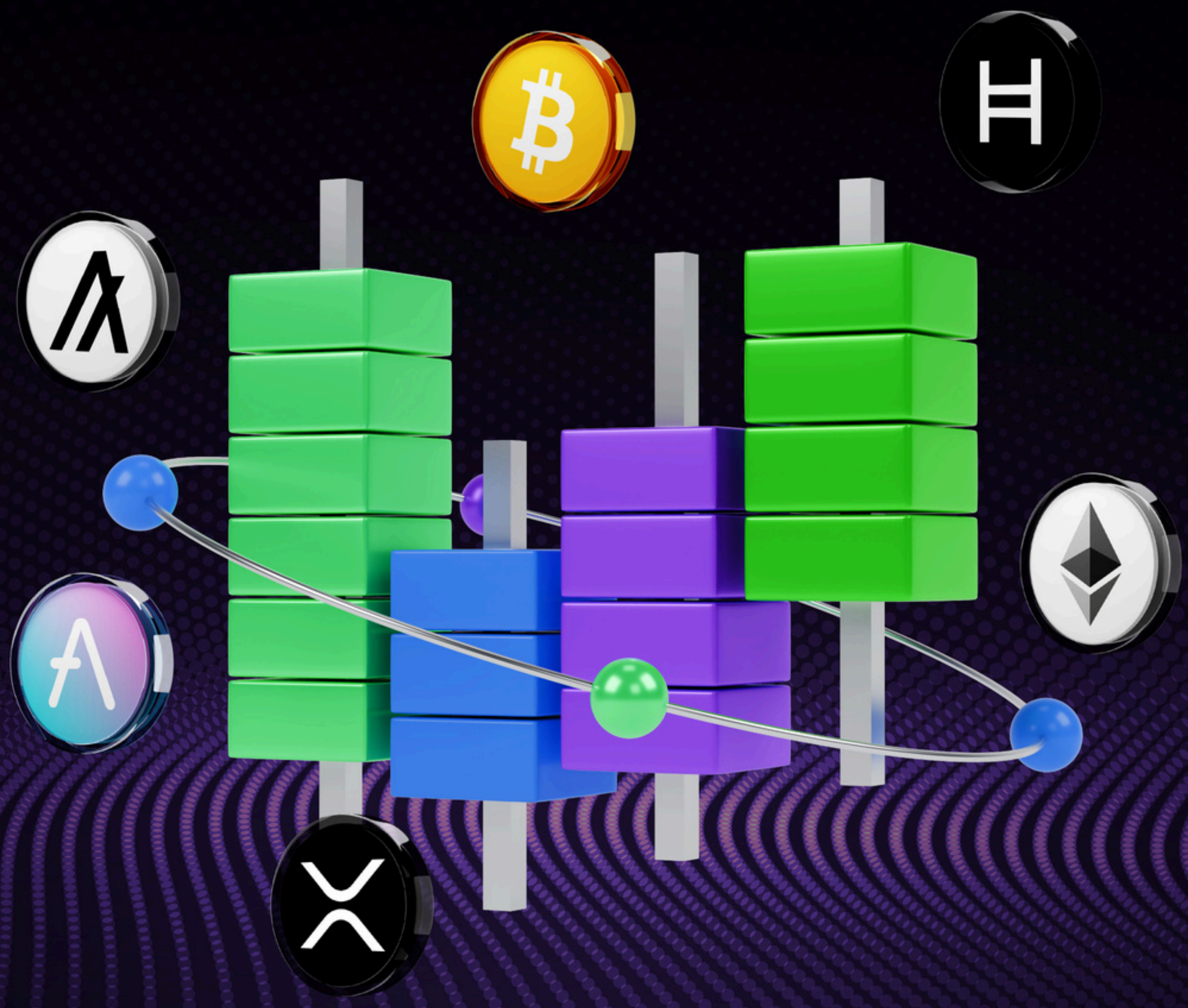

Index

Key Highlights

- This report applies **time-series clustering** to the **Nodiens Mood Index** to uncover common sentiment regimes across **67 crypto assets** and interpret **collective market psychology.**

- Using the **K-Shape clustering algorithm** on **21-day mood trajectories** assets were grouped by similarity in their sentiment evolution, revealing **three distinct behavioural regimes** — Panic & Rebound (V), Uptrend (Choppy), and Steady Drawdown.

- The results show that sentiment across assets remains **fragmented,** with optimism, fatigue, and recovery coexisting across different parts of the market — a hallmark of **transitional sentiment environments.**

- The findings highlight the **practical value of time-series clustering** for transforming complex, unstructured sentiment data into **actionable behavioural insights,** supporting **market monitoring, diversification, and early detection of mood shifts** among crypto assets.

Introduction

Understanding the emotional dynamics of the crypto market is increasingly critical for explaining short-term volatility and investor behaviour. Beyond price data, **sentiment indices** derived from online discussions, engagement tone, and community activity reveal collective mood cycles that can precede or accompany major market shifts. In behavioural finance, such sentiment-driven patterns often create self-reinforcing feedback loops of enthusiasm, panic, or apathy—phenomena documented in both equity and crypto markets [1–3].

To capture these dynamics systematically, this report applies **time-series clustering** to daily sentiment series. Time-series clustering is widely used to uncover latent regimes and recurring temporal patterns, with methods ranging from distance-based approaches (e.g., dynamic time warping, feature-space Euclidean, correlation distances) to model-based and deep learning techniques [4,5]. In financial contexts, these methods have been used to delineate market states, volatility regimes, and social-media-driven investor moods [6,7]. Here, we extend this idea to **emotion indices**, grouping similar sentiment trajectories into interpretable behavioural clusters.

We analyse the **Nodiens Mood Index,** a proprietary indicator that captures the prevailing sentiment surrounding each crypto asset. The index is derived from online community activity, discussion volume, and engagement tone, reflecting short-term emotional dynamics such as excitement, hype, or fear. Using this index, we identify clusters such as Steep Drawdown, Steady Uptrend, and Panic & Rebound, each representing a distinct emotional regime in the collective discourse. Unlike traditional market-state models, these clusters describe **how sentiment evolves,** not how prices move. Our analysis shows that assets frequently transition through recurring emotional patterns—fearful capitulations followed by optimism, steady confidence phases, and range-bound indecision.

This report delivers an interpretable framework for reading crowd psychology through short-term sentiment regimes. The goal is **contextual awareness**—recognising when markets appear emotionally overextended, fatigued, or primed for reversal. By classifying and interpreting sentiment clusters across the crypto universe, we aim to equip investors and traders with **behavioural intelligence** that complements traditional quantitative indicators and informs portfolio diversification, risk monitoring, and tactical decision-making.

Methodology and Data

Clustering Method: K-Shape

We employ **K-Shape** to cluster the Nodiens Mood Index time series according to their **overall shape** and **behavioural pattern** [8]. After z-normalising each series, similarity is measured using the Shape-Based Distance (SBD), which aligns a series y with a cluster centroid c by circularly shifting c to maximise their normalised cross-correlation (NCC):

$$SBD(y,\, c) \;=\; 1 \;-\; max_{\tau \in \{0,\ldots,T-1\}} NCC(y,\, shift(c,\, \tau)),$$

where is a circular shift aligning salient features.

The algorithm alternates two steps until convergence: **(1)** assign each series to the centroid with the smallest shape-based distance (highest aligned correlation), and **(2)** update the centroid by aligning all members and recomputing the dominant shape direction, then normalising it. This correlation-based alignment is efficient and produces clear, interpretable centroids that represent each cluster's typical pattern. Unlike elastic measures such as DTW [9], K-Shape's normalized cross-correlation alignment remains both robust and scalable while preserving interpretability [8].

Data and Sampling Design

We analyse **67 crypto assets** using the Nodiens Mood Index, applying the K-Shape clustering method to identify common sentiment trajectories. To illustrate the applicability of this approach, we focus on a **single randomly selected** date within October 2025. For this anchor date t, we construct a 21-day window [t−20, t] for every asset, producing an input matrix X(t) 6721. Each 21-day window is row-wise **z-normalised** [4]. A **21-day window** provides a balance between responsiveness to short-term sentiment shifts and stability for pattern recognition. Shorter windows (e.g., 7 or 14 days) tend to be overly reactive, while longer horizons dilute actionable local structure.

Determining the Number of Clusters

For each anchor date t and each candidate number of clusters K, we compute the **Silhouette Score** [10] using SBD as the distance metric:

$$s(i) \;=\; \frac{b(i) - a(i)}{max\{a(i),\, b(i)\}},$$

where a(*i*) is the average intra-cluster SBD for asset *i* and b(*i*) is the lowest average distance to any other cluster. Scores near +1 indicate well-separated clusters, values around 0 denote boundary cases, and negative scores imply potential misclassification. For each snapshot, we select the **K*** that **maximises the mean Silhouette Score** across all assets, allowing the model to adapt to the sentiment complexity of each time period.

Labelling Procedure

After K-Shape clustering, the resulting clusters and centroids are **unlabelled**. We assign interpretable behavioural names through a **feature-based rule schema.** Specifically, we use the Mood Index time series of each asset over its 21-day window to compute six descriptive shape features:

- **Trend slope** – overall upward or downward drift.
- **Change volatility** – standard deviation of daily level changes, distinguishing steady from choppy motion.
- **Curvature** – mean absolute second difference, identifying V or ∩ structures.
- **Monotonicity** – proportion of daily moves consistent with the overall trend, separating steady from noisy paths.
- **Half-slopes** – slope of the first and second halves of the window, detecting reversals.

These features capture whether the 21-day mood profile exhibits trends, reversals, or stable phases, enabling qualitative labelling of each cluster. At the cluster level, we compute the **median** of each feature across all members. Thresholds are **adaptive**, determined from the empirical distribution of these medians in each snapshot (e.g., quantile-based values for high/low slope, volatility, curvature). This approach maintains comparability across changing sentiment environments and avoids arbitrary global cut-offs. Table 1 summarises all possible behavioural labels and their qualitative meanings.

Label	Description
Panic & Rebound (V)	Sharp dip followed by clear recovery (capitulation → optimism)
Blow-off & Fade (∩)	Spike up followed by give-back (euphoria → fatigue)
Steep Uptrend	Fast, noisy rise
Steady Uptrend	Smooth, consistent rise
Uptrend (Choppy)	Rising overall with frequent whipsaws
Steep Drawdown	Fast, noisy decline
Steady Drawdown	Persistent, smoother decline
Drawdown (Choppy)	Falling overall with swings
Flat / Quiet	Little movement; low curvature
Range-Bound	Sideways, mean-reverting chop

Table 1. Behavioural labels and descriptions. In the presented analysis we focus only on the three types of behaviour that are bolded in the above table.

Implementation Summary

For the selected date, we (i) construct the 21-day window for each asset, (ii) apply z-normalisation, (iii) run K-Shape for a grid of candidate K, (iv) select K* via mean Silhouette Score, and (v) assign behavioural labels and extract cluster prototypes.

Key Findings

Cluster	Label	#	Assets
0	Panic & Rebound (V)	11	AAVE, ALGO, EOS, FLOW, GRT, HNT, LDO, MNT, OM, TON, XTZ
1	Uptrend (Choppy)	29	APT, **BCH**, BSV, **BTC**, CRO, **DOGE**, DOT, EGLD, ETC, **ETH**, FET, FIL, **HBAR**, JASMY, KCS, LTC, MKR, OKB, PEPE, PYTH, QNT, SAND, SHIB, **SOL**, UNI, **USDT**, XEC, **XLM**, XMR
2	Steady Drawdown	27	**ADA**, AKT, AR, ARB, ATOM, **AVAX**, BGB, **BNB**, CFX, FLR, GT, ICP, KAS, **LINK**, NEAR, NEO, RNDR, RUNE, SEI, STX, **SUI**, TAO, THETA, TIA, **TRX**, USDD, **XRP**

Table 2. Cluster composition for 21-day Mood windows (selected date: 2025-10-12; best K=3, mean Silhouette = 0.27, total number of assets = 67); assets with market capitalization above USD 8 billion as of 27/10/2025, are in bold.

The clustering analysis of Nodiens Mood Index for **12 October 2025** reveals three distinct sentiment regimes (Table 2). The first, **Panic & Rebound (V)**, reflects a sharp decline in sentiment followed by a recovery—signalling early-stage reversals where capitulation turns into renewed optimism. The second, **Uptrend (Choppy)**, captures a broad but uneven improvement in sentiment: markets are leaning positive, yet fluctuations remain frequent, suggesting cautious optimism and incomplete conviction. The third, **Steady Drawdown**, shows a smooth, persistent decline in sentiment, typical of longer fatigue phases where pessimism persists despite broader recovery elsewhere.

Overall, sentiment breadth is mixed. Nearly half of the assets (29/67) fall into **Uptrend (Choppy)**, indicating a generally positive mood with unstable confidence. Another 27 assets belong to **Steady Drawdown**, revealing a counter-current of persistent negativity concentrated among several major Layer-1 and infrastructure tokens—an insight valuable for relative sentiment positioning. The smaller **Panic & Rebound (V)** group (11 assets) marks tactical turnarounds that may either evolve into sustained optimism or fade if recovery momentum stalls.

Such sentiment snapshots offer several actionable insights for portfolio construction and tactical positioning. By interpreting cluster dynamics as behavioural regimes, investors and traders can better manage exposure, time entries, and anticipate shifts in market psychology.

- **Diversify by sentiment regime:** Avoid concentration within a single cluster. Combine exposure to Uptrend (Choppy) assets with limited hedges in Steady Drawdown names to balance optimism and downside protection.
- **Tactical timing:** Treat Panic & Rebound (V) clusters as potential entry zones but confirm the recovery—such as sustained higher lows in mood—before increasing risk exposure.
- **Relative positioning:** When the share of Uptrend (Choppy) assets expands, tilt portfolios toward these names; if Steady Drawdown assets grow in number, shift defensively or rebalance toward more resilient sentiment regimes.
- **Transition monitoring:** Track cluster migrations over time. Upgrades (Drawdown → Rebound → Uptrend) and downgrades (Uptrend → Drawdown) often precede broader narrative changes and can signal early turning points in collective market mood.

Conclusion

This analysis demonstrates how clustering of the Nodiens Mood Index can reveal distinct behavioural regimes that describe collective investor sentiment across the crypto market. By examining 21-day mood trajectories for 67 assets, various interpretable clusters can emerge —capturing phases of recovery, optimism, and fatigue. Although sentiment boundaries are naturally fluid, these clusters offer a valuable framework for interpreting market psychology in real time. These are significant signals that can be used for portfolio management and to manage risk related to these assets.

The findings highlight that sentiment analysis, when structured through time-series clustering, can complement traditional market metrics by identifying early signs of emotional turning points, regime transitions, and crowd behaviour shifts. Future iterations of this framework, extended to multiple dates or combined with price and volume data, could further enhance its predictive and diagnostic power for investors, traders, and market analysts seeking data-driven insight into crypto market mood.

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