

Advancing Space Situational Awareness and Geospatial Intelligence Through Density-Based Clustering Utilizing Machine Learning

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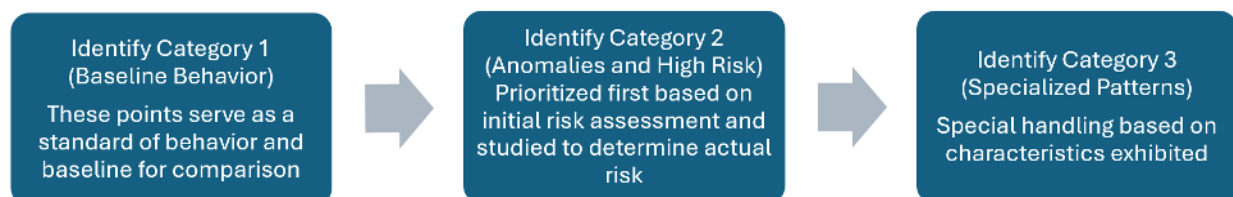
1. BLUF

- Density-Based Spatial Clustering of Applications with Noise (DBSCAN) successfully organized 30,052 orbital objects into 23 distinct clusters while identifying 4,098 objects (13.64%) as anomalous noise.
- Cluster 0 contains 22,481 objects (74.81% of the dataset) and establishes the baseline orbital population used for comparison against all other debris groups.
- Cluster -1 represents anomalous and potentially high-risk debris characterized by substantial variability across orbital parameters and unpredictable orbital behavior.
- Clusters 2, 4, and 8 demonstrate that specialized orbital populations exist and may require different monitoring, conjunction assessment, and mitigation approaches.
- The DBSCAN Cluster Prioritization Framework provides a systematic method for identifying and prioritizing potentially high-risk debris before conducting resource-intensive conjunction assessment activities.

2. Top-level Analysis

Earth's orbital environment has changed dramatically over the past decade. Prior to 2015 satellite launches between 200 and 1,750 km were government and communication focused. In recent years there has been a shift with commercial missions dominating launches (ESA Space Debris Office, 2024), driven by lower launch costs, advances in satellite technology, and growing commercial demand. With an estimated launch of 58,000 additional satellites expected by 2030 (United States Government Accountability Office, 2023), orbital congestion and collision risk continue to increase. More than 9,300 tons of material (European Space Agency, n.d.), and an estimated 128 million debris fragments already occupy Earth's orbit, many too small to track but still capable of damaging active spacecraft (IADC, 2024). As operators increasingly rely on fuel-intensive Predetermined Debris Avoidance Maneuvers (PDAMs), scalable approaches to prioritizing conjunction risk become essential. Boosted by machine learning, DBSCAN organizes large orbital debris datasets into operationally meaningful categories. Analysis of the December 2024 Space-Track catalog identified distinct debris populations that support conjunction assessment, debris mitigation, and resource allocation through the DBSCAN Cluster Prioritization Framework.

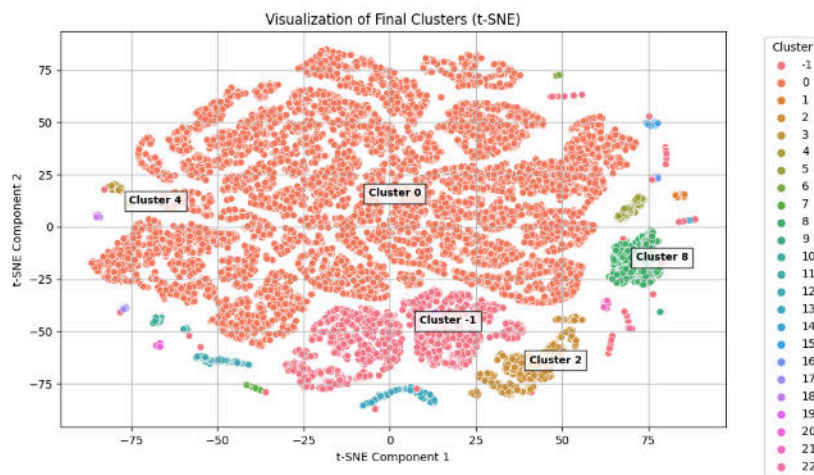
Figure 1. The DBSCAN Cluster Prioritization Framework



3. Secondary Analysis

DBSCAN identified three categories of orbital debris: Baseline Behavior (Cluster 0), Anomalies and Potential High-Risk Debris (Cluster -1), and Specialized Patterns (Clusters 2, 4, and 8). Figure 2 illustrates the separation of these populations, demonstrating that orbital objects can be systematically organized into operationally meaningful groups rather than treated as a single homogeneous debris field. Cluster 0 represented 74.81% of all objects and established the baseline population for comparison. Cluster -1 exhibited substantial variability across orbital parameters and a dispersed distribution, supporting its classification as anomalous and potentially higher-risk debris. In contrast, Clusters 2, 4, and 8 formed compact, well-defined orbital populations with distinct characteristics. Cluster 2 exhibited relatively low variability across multiple orbital parameters, indicating a well-defined orbital population. Cluster 4 exhibited the greatest deviation in eccentricity, while Cluster 8 displayed distinct inclination and RAAN characteristics, supporting specialized conjunction assessment and debris mitigation approaches.

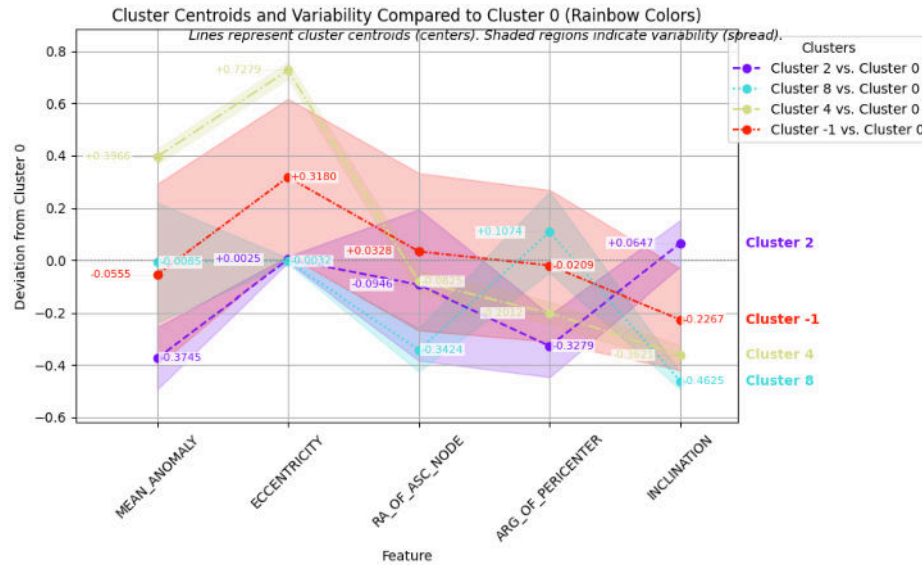
Figure 2. Visualization of Final Clusters (t-SNE)



Collectively, these findings support the DBSCAN Cluster Prioritization Framework demonstrating that orbital debris can be categorized into operationally meaningful populations that enable analysts to prioritize monitoring efforts, focus computational resources on potentially higher-risk objects, and improve conjunction assessment efficiency.

Figure 3 further substantiates these distinctions by comparing cluster centroids and variability relative to Cluster 0, the baseline population. Cluster 2 exhibited relatively low variability across the evaluated orbital parameters, indicating a fairly consistent and well-defined orbital population. Cluster 4 demonstrated the greatest positive deviation in eccentricity, distinguishing it from the baseline population. Cluster 8 exhibited distinct inclination and RAAN characteristics with comparatively low variability, while Cluster -1 displayed elevated variability across multiple orbital parameters, supporting its classification as an anomalous and potentially higher-risk debris population.

Figure 3. Cluster Centroids and Variability Compared to Cluster 0



4. Impact

The DBSCAN Cluster Prioritization Framework demonstrates how machine learning can improve Space Situational Awareness (SSA) and GEOINT by organizing 30,052 orbital objects into operationally meaningful categories before conjunction assessment. Rather than treating the orbital catalog as a single homogeneous dataset, analysts can distinguish baseline orbital behavior from anomalous and specialized populations, enabling more targeted monitoring, conjunction assessment prioritization, debris mitigation planning, and resource allocation. As orbital catalogs continue to expand, this preprocessing approach has the potential to reduce computational burden while improving the efficiency and consistency of analytical workflows.

This assessment demonstrates professional tradecraft competencies in Analysis Tools and Machine Learning within the USGIF Emerging Build Knowledge (EBK) framework through the operational application of unsupervised machine learning to a GEOINT and SSA problem. The results support piloting the DBSCAN Cluster Prioritization Framework within operational conjunction assessment and risk prioritization processes.

5. Confidence

High Confidence: This assessment is based on a structured and reproducible analysis of 30,052 orbital objects from the December 2024 Space-Track catalog. Internal validity was strengthened through data cleaning, preprocessing, feature selection, log transformations, normalization, and iterative parameter tuning using grid search, k-distance plots, and silhouette score analysis. The optimized DBSCAN parameters ($\epsilon = 0.13$, $\text{min_samples} = 25$) produced a silhouette score of 0.56, and evaluation confirmed that observed clustering differences were attributable to systematic parameter adjustments rather than inconsistencies in the dataset or analysis methods.

External validity was reinforced using the Space-Track catalog and adherence to the Consultative Committee for Space Data Systems (CCSDS) Orbit Mean-Elements Message (OMM) standard, supporting data integrity, interoperability, transparency, and reproducibility.

6. Bias

Methodological bias was mitigated through systematic data preprocessing and focusing on variables that could influence clustering based on prior knowledge rather than orbital behavior. Variables including OBJECT_TYPE and NORAD_CAT_ID, were excluded during clustering and used only for post-cluster interpretation and validation. Additional metadata and administrative fields (ex., COUNTRY_CODE, CLASSIFICATION_TYPE, OBJECT_NAME, and launch history) were also excluded because they do not describe orbital behavior. The assessment remains limited to the publicly available Space-Track catalog and therefore reflects only trackable orbital objects rather than the complete orbital debris environment, including the millions of smaller debris fragments that cannot be routinely tracked but still pose operational risk. As orbital congestion continues to increase, future research should evaluate the DBSCAN Cluster Prioritization Framework using time-series orbital data to assess cluster evolution over time, investigate adaptive clustering methods such as Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) and DBSCAN++, and explore integration with commercial SSA platforms and multi-source data to improve conjunction assessment, debris mitigation, and operational decision-making.

References

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