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USING APPARENT MOTION PARAMETERS AS FEATURES FOR MACHINE LEARNING-BASED TRACKLET ASSOCIATION: AN ANALYSIS OF FEATURE DISCRIMINATIVE POWER

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STATEMENT OF THE PROBLEM

Spacecraft fragmentation events generate dense swarms of debris fragments moving along closely spaced trajectories. Optical observations of such regions result in a large number of short observational arcs.

These short arcs, known as tracklets, are recorded as dense positional series $(\alpha(t), \delta(t))$ over a few seconds to minutes.

The challenge is to identify and link tracklets that belong to the same physical object, forming continuous object chains.

Traditional methods rely on preliminary orbit determination, yet they struggle in dense debris environments due to the excessive generation of false associations, while the complexity of the underlying orbital algorithms imposes a heavy computational cost that hinders real-time processing.

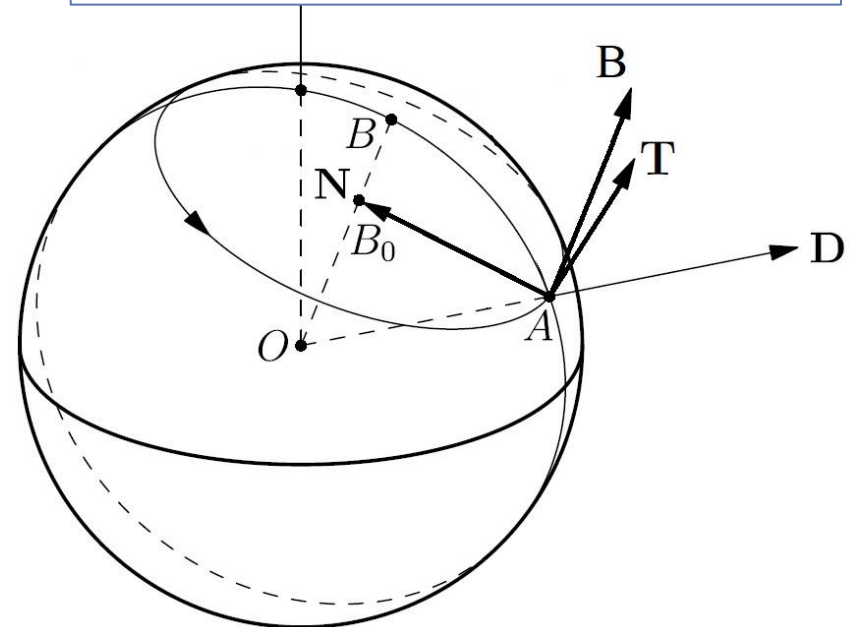
Goal: Develop a fast, reliable, **orbit-independent** approach to tracklet association, leveraging the direct geometric and kinematic information embedded within the tracklets themselves.

APPARENT MOTION PARAMETERS (AMPs) AS AN ALTERNATIVE

Mathematical Basis: The apparent trajectory of a space object on the celestial sphere is locally approximated by an osculating small circle. The AMPs describe the local kinematics of the object through the geometry of this osculating small circle.

Core Idea: Instead of solving the inverse orbital problem, we use dense coordinate series $(\alpha(t), \delta(t))$ to compute AMPs. These parameters describe the position, velocity, and acceleration of the object on the celestial sphere, projected onto the natural axes: the tangent **T** (direction of velocity), the principal normal **N** (towards the center of curvature B_0), and the binormal **B** = **T** × **N**. Additionally, the figure shows the direction vector **D** (normal to the celestial sphere).

The geometrical points denote:
O – the center of the celestial sphere (observer's origin);
A – the current observation point on the apparent trajectory;
B – the pole of the osculating small circle.



APPARENT MOTION PARAMETERS (AMP) AS AN ALTERNATIVE

Based on the natural frame defined in the previous slide, the Apparent Motion Parameters (AMPs) are directly derived from the positional series $(\alpha(t), \delta(t))$:

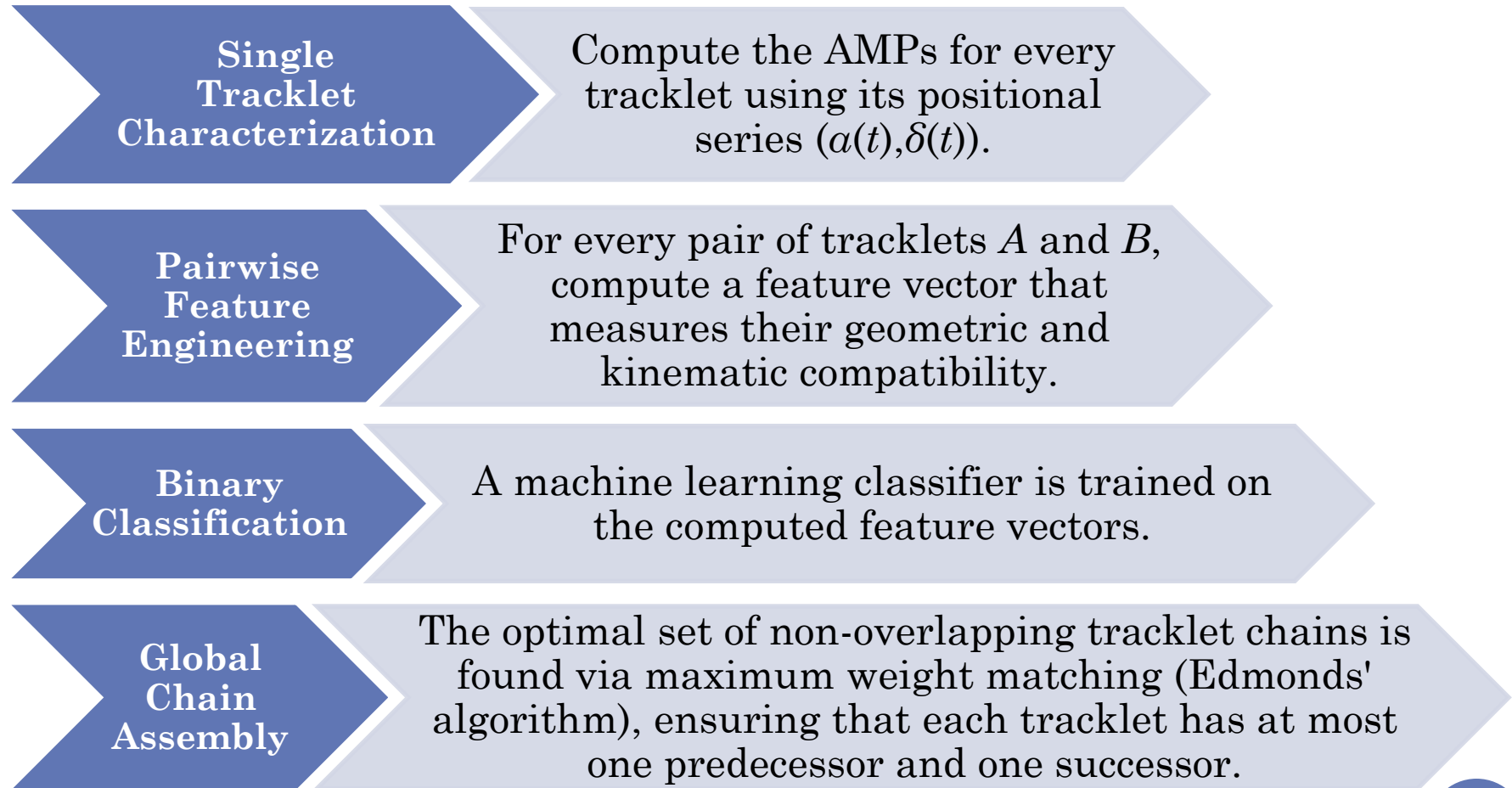
- **First-order parameters** define the velocity vector $\mathbf{T}$: the angular topocentric velocity $\boldsymbol{\mu}$ provides its magnitude, while the position angle ψ specifies its orientation relative to the declination circle on the celestial sphere.
- **Second-order parameters** determine the acceleration vector: the rate of change of the angular velocity $\dot{\boldsymbol{\mu}}$ defines the tangential component (along the tangent vector $\mathbf{T}$), whereas the geodesic curvature κ characterizes the normal component (directed along the principal normal $\mathbf{N}$, toward the center of curvature B_0).

Geometric configuration of the osculating small circle is defined by the normal vector $\mathbf{P}$ (pointing to the pole B , aligning with the binormal $\mathbf{B}$) and the distance parameter p , which determines the separation between the center of the sphere O and the plane of the small circle.

Key Advantage: Computing AMPs requires neither a preliminary orbit determination, nor an initial state vector, nor prior knowledge of the physical motion model. The only requirement is the smoothness (differentiability) of the trajectory on the celestial sphere over the observation interval, making the method computationally lightweight and efficient.

PROPOSED METHODOLOGY FOR TRACKLET ASSOCIATION

The methodology follows a four-stage pipeline directly derived from the AMPs:



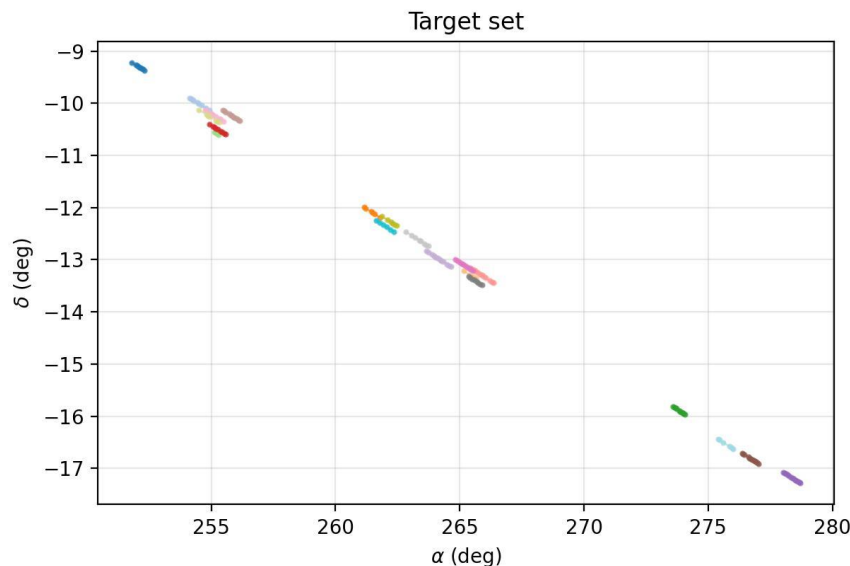
OBSERVATIONAL DATA

Training set: Composed of 840 tracklets obtained in 2022–2023 at the Crimean Astrophysical Observatory: **363 tracklets** belong to **168 distinct objects** observed over a single night (2–7 tracklets per object). The remaining **477 tracklets** from the same nights provide diverse false associations. Pairs were generated with two constraints:

- **no temporal overlap** between tracklets;
- **time difference** between epochs not exceeding **10 hours**.

Pairs generated: 5,315 (238 true, 5,077 false).

Class imbalance is significant (true pairs are ~20 times fewer).



Target set: Contains 20 tracklets from an 80-minute observation session of a debris cloud (ATLAS 5 CENTAUR R/B breakup, September 2024).

Pairs generated: 183 (18 true, 165 false).

The author thanks **Vasiliy V. Rumyantsev**, senior researcher at CrAO RAS, for providing the observational data.

STEP 1: APPARENT MOTION PARAMETERS (AMPs) FOR A SINGLE TRACKLET

For each input tracklet $(t_j, \alpha_j, \delta_j)$, $j=1, \dots, n$, the following parameters are computed at the mean observation epoch $t_0 = (t_1 + t_n)/2$:

- **D** – direction vector to the observed object (unit radius vector);
- **T** – tangent vector (direction of motion);
- μ – angular topocentric velocity;
- ψ – position angle (orientation relative to the declination circle);
- κ – geodesic curvature (characterizing the normal acceleration);
- **P** – normal vector to the osculating small circle plane – defines the pole of the small circle closest to it;
- **p** – distance parameter of the osculating small circle – the length of the vector directed along **P** from the center of the celestial sphere to the center of the small circle.

The calculation algorithm is described in detail in the textbook
"Direct Methods for Determining the Orbits of Celestial Bodies"
by **Bykov O.P.** and **Kholshevnikov K.V.**
Izd-vo S.-Peterb. un-ta, (2013) [in Russian].

STEP 2: PAIRWISE FEATURE ENGINEERING

For each pair of tracklets A and B , a comprehensive set of candidate features was computed based on their positional series $(\alpha(t), \delta(t))$ and AMPs. The full list of investigated features includes:

1. Joint Approximation Residuals (6 features):

- σ_{line} – residual of the geometric trajectory $\delta(\alpha)$;
- σ_α and σ_δ – residuals of temporal dependencies $\alpha(t)$ and $\delta(t)$;
- σ_{D1} , σ_{D2} , σ_{D3} – residuals for the direction cosines $D_1(t)$, $D_2(t)$, $D_3(t)$.

2. Geometric & Kinematic Parameters based on AMPs (7 features):

- α_{align} – alignment angle between displacement and mean tangent;
- R_{sep} – ratio of measured angular separation to expected separation;
- $\Delta\psi$ – difference in position angles;
- θ_P – angle between normals to the osculating small-circle planes;
- Δp – difference in the distance parameters of the small circles;
- $\Delta\mu$ – difference in angular topocentric velocities;
- $\Delta\kappa$ – difference in geodesic curvatures.

3. Auxiliary Parameters (2 features):

- Δt_{AB} – time interval between tracklet mean epochs;
- ρ_{AB} – angular separation between mean positions.

A detailed separability analysis of these candidate features will be presented on the following slides, leading to the selection of an optimal compact set.

JOINT APPROXIMATION RESIDUALS

Concept: For each pair of tracklets A and B , we merge their observational data into a single series and fit a **second-degree polynomial** to the combined set of points using the **least-squares method**.

Feature definition: The feature σ is the **RMS (Root Mean Square) residual** of this polynomial fit:

$$\sigma = \sqrt{\frac{\sum_{j=1}^n (\text{residual}_j)^2}{n}},$$

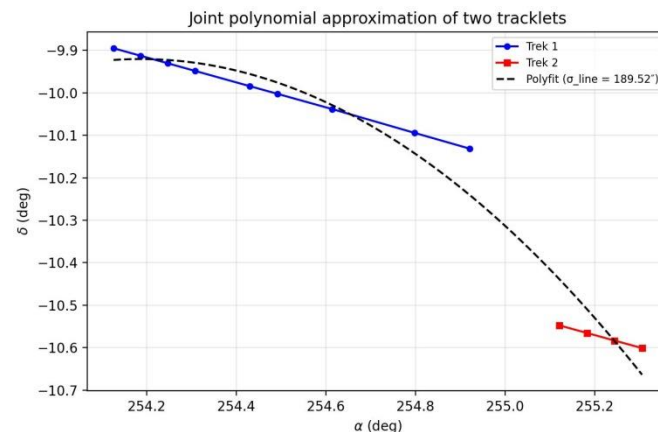
where n is the number of merged data points.

It measures the average deviation of the observed points from a smooth common trajectory.

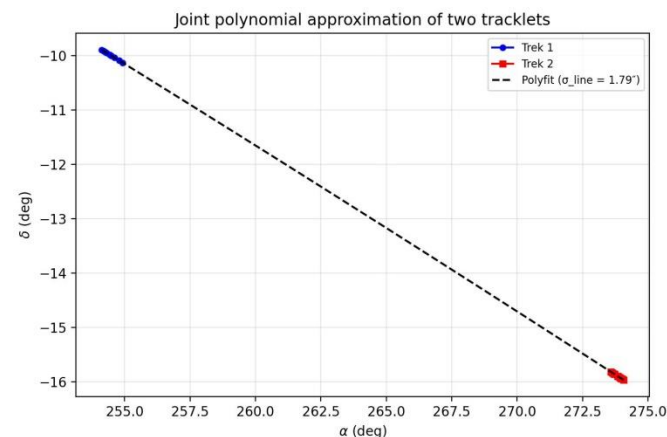
Expected values: For true pairs, residuals are typically **a few arcseconds**. For false pairs, they are orders of magnitude larger.

This procedure is applied to **6 different data representations** ($\delta(\alpha)$, $\alpha(t)$, $\delta(t)$, $D_1(t)$, $D_2(t)$, and $D_3(t)$), giving us the six approximation residual features.

Example of a False Pair ($\sigma_{\text{line}}=189.52''$)



Example of a True Pair ($\sigma_{\text{line}}=1.79''$)



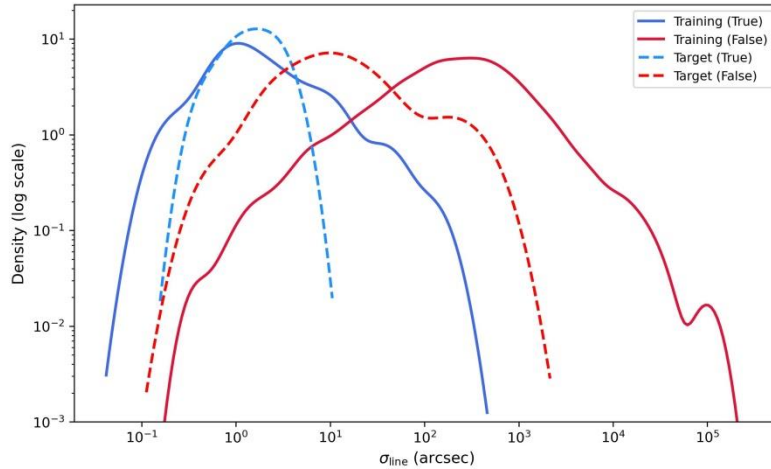
DISTRIBUTIONS: JOINT APPROXIMATION RESIDUALS

The joint approximation residuals provide strong discriminative power. The table shows the percentage of pairs with RMS residuals below 30" for all six residual features on the training set:

Feature	True Pairs	False Pairs
σ_{line}	96.2%	11.5%
σ_{α}	71.0%	2.4%
σ_{δ}	78.2%	10.2%
σ_{D1}	82.8%	11.6%
σ_{D2}	86.1%	3.9%
σ_{D3}	90.8%	9.6%

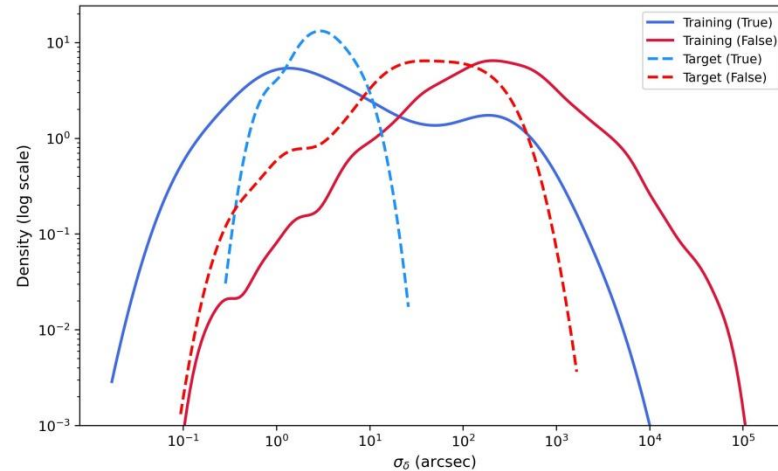
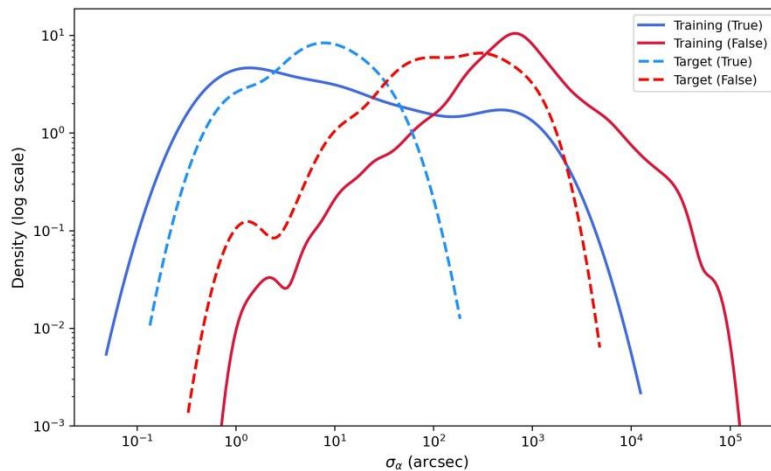
DISTRIBUTIONS: σ_{line} , σ_{α} and σ_{δ}

σ_{line} – residual of the geometric trajectory $\delta(\alpha)$



High Separability: For true pairs (blue curves), the residuals are extremely small, with peaks located between **1 and 10 arcsec**. In contrast, false pairs (red curves) show residuals that are **orders of magnitude larger**, peaking between 10^2 and 10^3 arcsec.

σ_{α} and σ_{δ} – residuals of temporal dependencies $\alpha(t)$ and $\delta(t)$

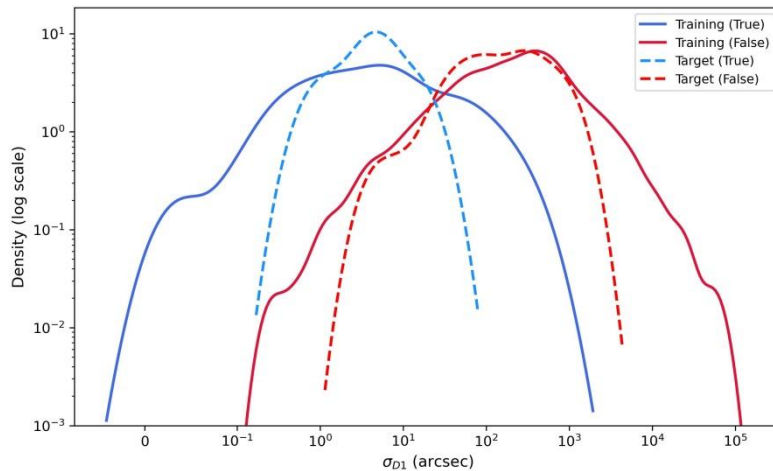


Note on plots: These Kernel Density Estimation (KDE) plots display smoothed probability densities on a logarithmic vertical axis to highlight the relative proportions of true versus false associations, with feature values in arcseconds plotted on a logarithmic horizontal scale.

DISTRIBUTIONS: σ_{D1} , σ_{D2} and σ_{D3}

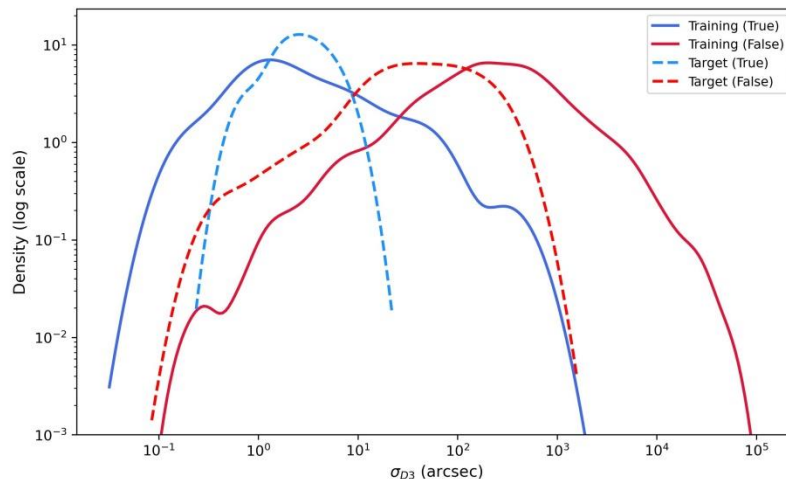
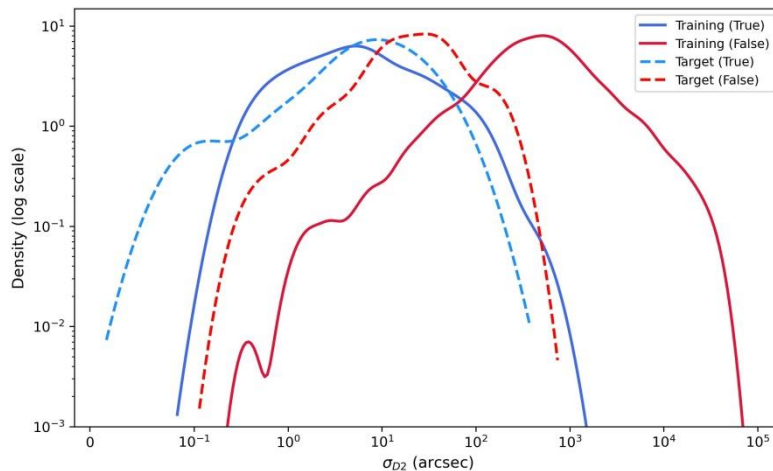
The direction cosines are computed from the topocentric equatorial coordinates using the standard formulas: $D_1 = \cos\delta \cos\alpha$, $D_2 = \cos\delta \sin\alpha$, $D_3 = \sin\delta$.

The features σ_{D1} , σ_{D2} , σ_{D3} represent the RMS residuals of a second-degree polynomial fit to these components as a function of time t .



The plots demonstrate the same clear separation observed for the previous approximation residuals. True pairs (blue curves) are strongly concentrated at residual values below 10 arcsec.

In contrast, false pairs (red curves) are shifted toward values that are orders of magnitude larger, typically exceeding 10^2 arcsec.



Note on plots: These Kernel Density Estimation (KDE) plots display smoothed probability densities on a logarithmic vertical axis to highlight the relative proportions of true versus false associations, with feature values in arcseconds plotted on a logarithmic horizontal scale.

DISTRIBUTIONS: α_{align}

α_{align} – Alignment Angle between displacement and mean tangent:

$$\alpha_{\text{align}} = \frac{180}{\pi} \arccos \left(\frac{|(\mathbf{D}_B - \mathbf{D}_A) \cdot \mathbf{T}_{\text{mean}}|}{|\mathbf{D}_B - \mathbf{D}_A|} \right), \quad \mathbf{T}_{\text{mean}} = \frac{\mathbf{T}_A + \mathbf{T}_B}{|\mathbf{T}_A + \mathbf{T}_B|}.$$

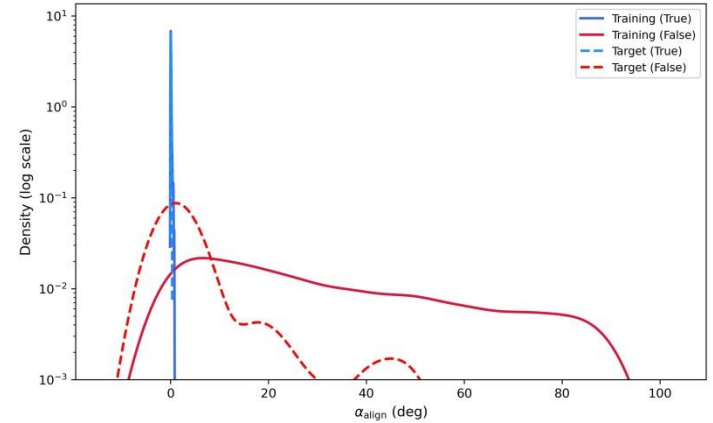
This feature measures the degree of collinearity between the displacement vector of two tracklets and their mean direction of motion.

Expected Values & Distribution:

For a **true pair**, the displacement vector $\mathbf{D}_B - \mathbf{D}_A$ should be nearly collinear with the direction of motion $\mathbf{T}_{\text{mean}}$.

Thus, α_{align} should be **close to 0°**.

Graph analysis: The plot confirms an exceptionally sharp and narrow peak for true pairs at 0° (blue curves). False pairs (red curves) yield a broad, spread-out distribution with low density at 0°.



Quantitative result: On the training set, 100% of true pairs have $\alpha_{\text{align}} < 0.75^\circ$; in 76.4% of cases, it does not exceed 0.1° .

Conclusion: The excellent agreement between the solid (Training) and dashed (Target) blue curves confirms the feature is highly stable, generalizes well, and serves as the **most discriminative feature** in our study.

Note on plots: These Kernel Density Estimation (KDE) plots display smoothed probability densities on a logarithmic vertical axis to highlight the relative proportions of true versus false associations, with feature values in degrees plotted on a horizontal scale.

DISTRIBUTIONS: R_{SEP}

R_{sep} – ratio of measured angular separation to expected separation:

$$R_{\text{sep}} = \frac{\rho_{AB}}{\frac{1}{2}(\mu_A + \mu_B) \cdot \Delta t_{AB}},$$

where ρ_{AB} is the angular separation between the mean position vectors $\mathbf{D}_A$ and $\mathbf{D}_B$, μ_A and μ_B are the angular velocities, and Δt_{AB} is the time interval between their mean epochs.

This feature measures the consistency of the apparent angular motion. It verifies whether the angular distance traveled between two tracklets matches the expected distance derived from their topocentric angular velocities and time Δt_{AB} .

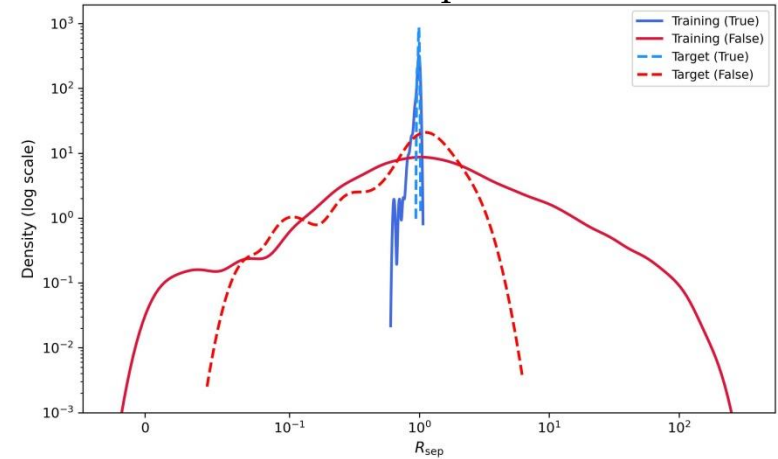
Expected Values & Distribution:

For a **true pair** belonging to the same object, the angular motion is nearly uniform over the observation interval; thus, R_{sep} should be **close to 1.0**.

Graph analysis: True pairs (blue curves) form an exceptionally sharp, spike-like peak precisely at $R_{\text{sep}}=1.0$. False pairs (red curves) display a broad, diffuse distribution extending over several orders of magnitude.

Quantitative result: On the training set, R_{sep} lies in the narrow interval (0.90,1.01) for **92%** of true pairs, compared to only **5.2%** of false pairs.

Conclusion: The striking separation between the needle-sharp blue peak and the broad red tail confirms that R_{sep} is a highly reliable geometric criterion. The excellent agreement between the solid (Training) and dashed (Target) curves further validates its stability and robustness.



DISTRIBUTIONS: DIFFERENCE IN POSITION ANGLES $\Delta\psi$

$$\Delta\psi = \frac{180}{\pi} \min(|\psi_A - \psi_B|, 2\pi - |\psi_A - \psi_B|) \quad [\text{deg}].$$

This feature measures the consistency of the direction of apparent motion. It represents the angular difference between the tangent vectors $\mathbf{T}_A$ and $\mathbf{T}_B$ at the mean epochs of two tracklets.

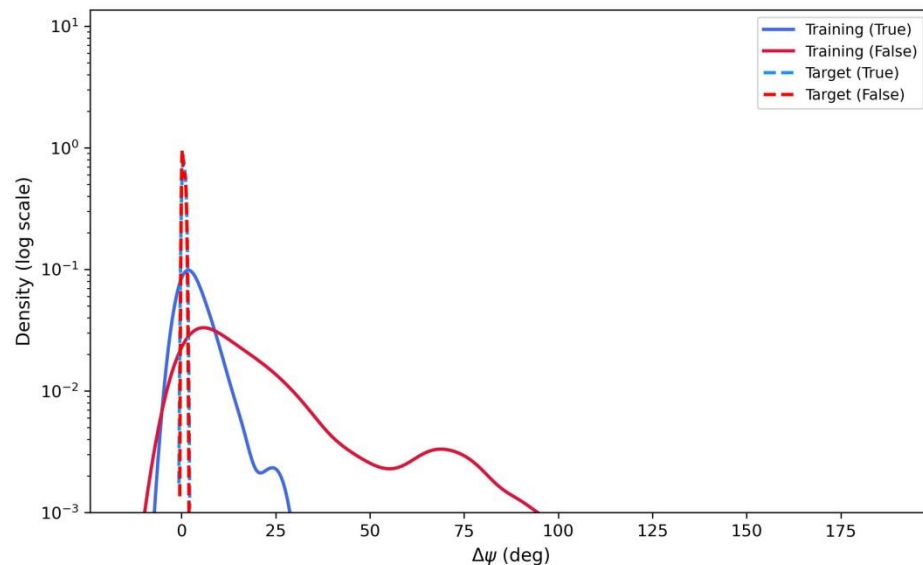
Expected Values & Distribution:

For **true pairs**, the apparent motion directions must be consistent. Thus, $\Delta\psi$ is strongly concentrated near 0° . However, due to the topocentric effect (loops in the apparent trajectory), larger values are possible – for example, a true pair with $\Delta\psi \approx 95^\circ$ was recorded in the training set.

Graph analysis: In the training set, true pairs (blue curves) demonstrate a narrow peak near 0° , whereas false pairs (red curves) exhibit a broader distribution. The target distributions (dashed lines) appear sharper and sit closer to 0° than the training distributions (solid lines).

Quantitative result: On the training set, $\Delta\psi < 5^\circ$ for 71% of true pairs compared to only 24% of false associations.

Conclusion: The informative value of this feature decreases in dense swarms of fragments observed over a short period of time. However, it can be useful when analyzing observations obtained throughout the night.



DISTRIBUTIONS: θ_P AND Δp – CONSISTENCY OF SMALL-CIRCLE PLANES

$$\theta_P = \arccos(|\mathbf{P}_A \cdot \mathbf{P}_B|) \quad [\text{deg}], \quad \Delta p = |p_A - p_B|.$$

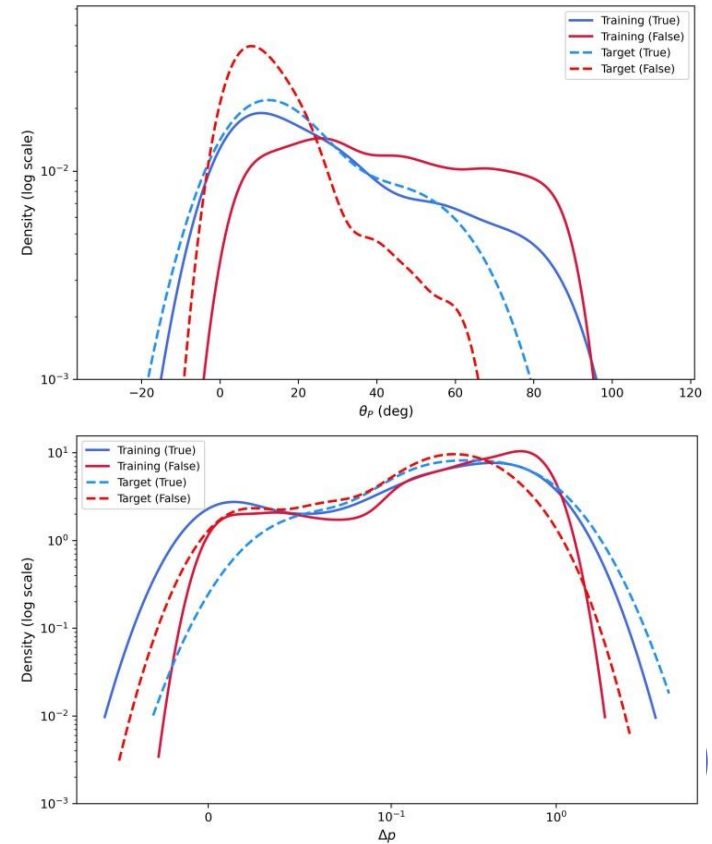
- θ_P – The angle between the normals $\mathbf{P}_A$ and $\mathbf{P}_B$ to the osculating small-circle planes. If the tracklets belong to the same object, the normals should coincide, yielding $\theta_P \approx 0^\circ$;
- Δp – The difference between the distance parameters p_A and p_B of the small circles. True pairs should exhibit very similar p values.

Анализ графиков :

θ_P plot: The distributions of true pairs (blue curves) and false pairs (red curves) show **significant overlap**. They peak in similar regions, offering very poor discriminative power.

Δp plot: The separation is even worse; the blue and red curves **overlap almost completely** across the entire range. This feature fails to separate the two classes entirely.

Conclusion: Due to the short length of our tracklets, the derived planes of the osculating small circles are **highly sensitive to measurement noise**. Consequently, θ_P and Δp act as unreliable criteria and demonstrate low discriminative power.



DISTRIBUTIONS: $\Delta\mu$ AND $\Delta\kappa$ – KINEMATIC DIFFERENCES

$$\Delta\mu = |\mu_A - \mu_B| \quad [\text{arcsec/sec}], \quad \Delta\kappa = |\kappa_A - \kappa_B|.$$

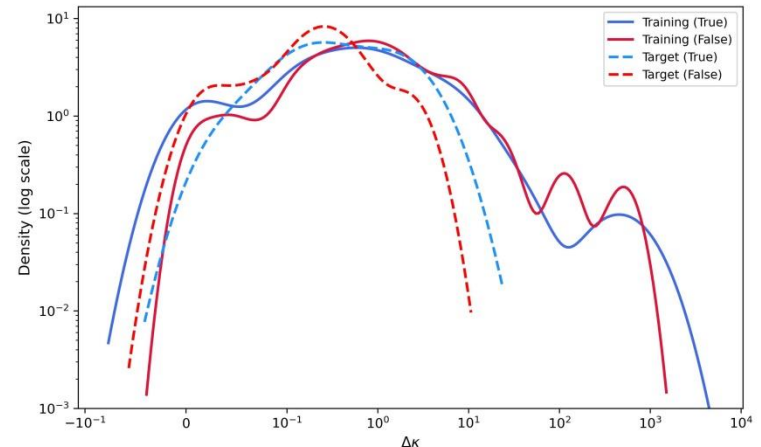
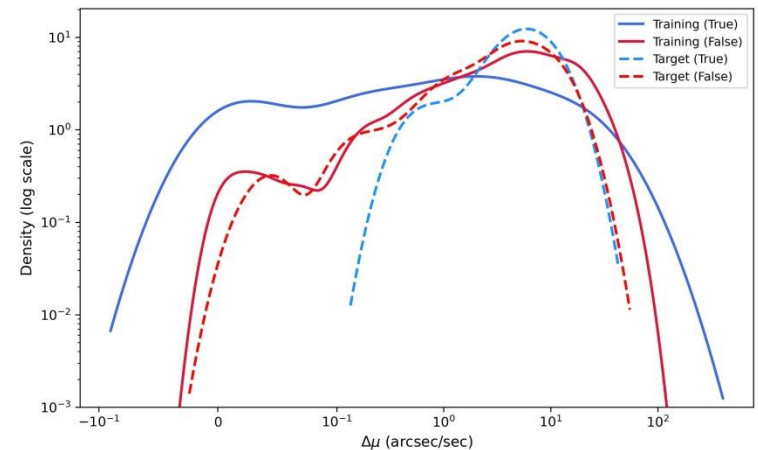
- $\Delta\mu$ – The difference between the angular topocentric velocities μ_A and μ_B of the two tracklets. For a true pair, the angular speed should be nearly identical, so $\Delta\mu \approx 0$;
- $\Delta\kappa$ – The difference between the geodesic curvatures κ_A and κ_B . True pairs should trace similar arcs on the celestial sphere, resulting in small differences in curvature.

Graph Analysis & Reason for Rejection:

$\Delta\kappa$ plot: The distributions of true pairs (blue) and false pairs (red) **overlap almost completely**. This indicates that the geodesic curvature is extremely sensitive to measurement noise on short observational arcs, making it an unreliable discriminator.

$\Delta\mu$ plot: Similar to $\Delta\kappa$, there is a strong overlap between the classes.

Conclusion: Both features provide low or completely absent discriminative power.



DISTRIBUTIONS: Δt_{AB} AND ρ_{AB} – AUXILIARY FEATURES

$$\Delta t_{AB} = |t_{0,A} - t_{0,B}| \quad [\text{sec}], \quad \rho_{AB} = \arccos(\mathbf{D}_A \cdot \mathbf{D}_B) \quad [\text{arcsec}]$$

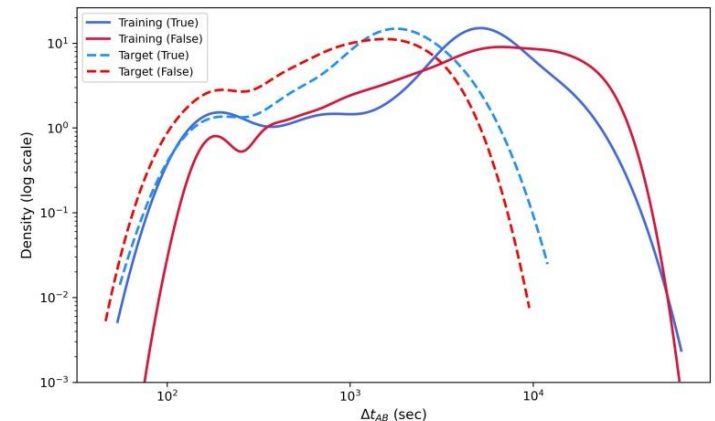
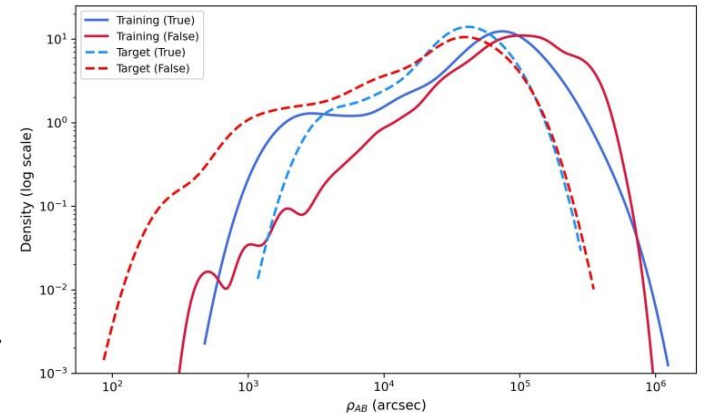
Δt_{AB} – the time interval between the mean observation epochs of tracklets A and B ;
 ρ_{AB} – the angular separation between the mean direction vectors $\mathbf{D}_A$ and $\mathbf{D}_B$ of the two tracklets.

Graph Analysis:

The wide, overlapping distribution of both characteristics reflects the **representativeness of the sample**: true and false pairs occur over a wide range of time intervals and angular distances.

Potential utility: In principle, raw contextual features like these could provide auxiliary information, since ensemble ML methods are capable of capturing non-linear interdependencies when combined with other characteristics. However, including the auxiliary parameters Δt_{AB} and ρ_{AB} in the feature space did not provide improvements in classification or chain assembly.

Conclusion: The potential usefulness of these parameters requires further investigation.



FINAL FEATURE SET

After evaluating all 15 candidate features, we selected a compact set of **9 features** that provides optimal discriminative power and generalization capability:

1. Joint Approximation Residuals (6 features):

$$\sigma_{\text{line}}, \sigma_{\alpha}, \sigma_{\delta}, \sigma_{D1}, \sigma_{D2}, \sigma_{D3};$$

2. Geometric Criteria derived from AMPs (3 features):

$$\alpha_{\text{align}}, R_{\text{sep}}, \Delta\psi.$$

Why this set?

High separability: As shown on previous slides, these features exhibit minimal overlap between true and false distributions.

Stability (except for $\Delta\psi$): They demonstrate consistent behavior between Training and Target datasets (minimal data shift).

Completeness: The six residual features account for the smoothness of the trajectory, while the three geometric criteria characterize its spatial configuration and kinematics.

STEP 3: BINARY CLASSIFICATION

Problem Formulation: The tracklet association task is reduced to a binary classification problem. A pair is assigned to **Class 1** (true association) if the two tracklets belong to the same physical object, and to **Class 0** (false association) otherwise.

Algorithms: Three classifiers were trained on the 9-feature vectors:

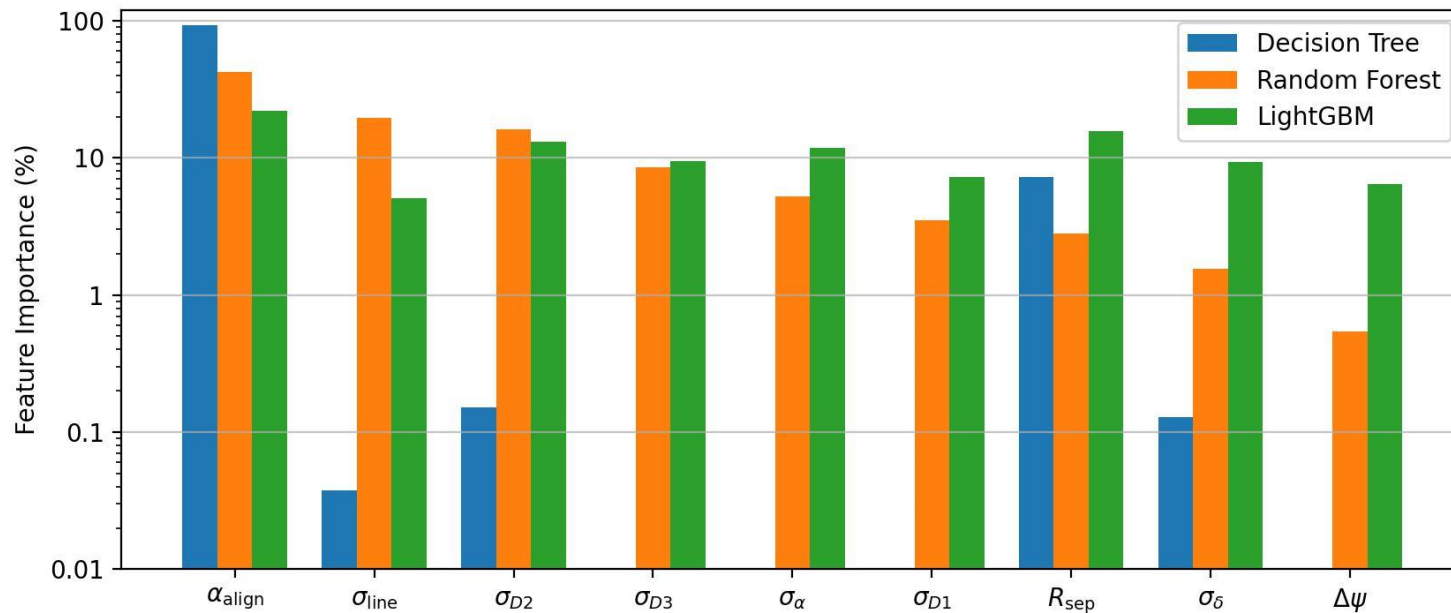
- Decision Tree (DT);
- Random Forest (RF);
- LightGBM gradient boosting.

Dataset & Imbalance: The training set consists of **5,315 pairs**. Due to the extreme class imbalance (5,077 false vs. 238 true pairs), class weights were applied during training to compensate for the minority class.

Training Procedure: The dataset was split into a **75% training and 25% testing** subset. Optimal hyperparameters were found via cross-validation, with the objective of maximizing the **Area Under the Precision-Recall curve (AUC-PR)**.

Output: Each trained classifier outputs a probability p_{AB} that a pair belongs to the same object. A pair is considered a true association if $p_{AB} \geq 0.5$.

FEATURE IMPORTANCE ANALYSIS



The bar chart illustrates the relative importance (%) of the nine features for all three trained ML models, sorted by Random Forest importance.

Decision Tree: α_{align} is overwhelmingly dominant (92.4%), followed by R_{sep} (7.3%). All other features are nearly ignored.

Random Forest: The importance of α_{align} decreases to 42.2%. Approximation residuals gain significant weight: σ_{line} (19.6%), σ_{D2} (16.2%), and σ_{D3} (8.5%).

LightGBM: The most balanced distribution: α_{align} (21.9%), R_{sep} (15.7%), σ_{D2} (13.1%), and σ_{α} (11.8%). The remaining features contribute between 5% and 9.5%.

Conclusion: Ensemble methods (RF and LightGBM) utilize a wide spectrum of features – combining geometric criteria with trajectory smoothness – resulting in a significantly better Precision–Recall balance compared to a single Decision Tree.

PERFORMANCE COMPARISON ON THE TEST SET

Metric	Decision Tree	Random Forest	LightGBM
Precision	0.882	0.906	0.870
Recall	1.000	0.967	1.000
False Positives (FP)	8	6	9
False Negatives(FN)	0	2	0
AUC-PR	0.980	0.989	0.987

All three models achieve exceptional performance on the test dataset, with AUC-PR scores exceeding 0.98. Random Forest achieves the best balance, yielding the highest Precision (0.906) and the lowest number of False Positives (6). Decision Tree and LightGBM successfully capture all true associations (Recall = 1.0), but at the cost of slightly reduced Precision, while Random Forest misses 2 true pairs.. It is important to note that these high metrics are obtained on the test set, which is a direct subset of the training distribution.

PERFORMANCE COMPARISON ON THE TARGET SET

Metric	Decision Tree	Random Forest	LightGBM
Predicted Positives	37	38	55
Precision	0.487	0.474	0.327
Recall	1.000	1.000	1.000
False Positives (FP)	19	20	37
False Negatives (FN)	0	0	0
AUC-PR	0.713	0.936	0.949

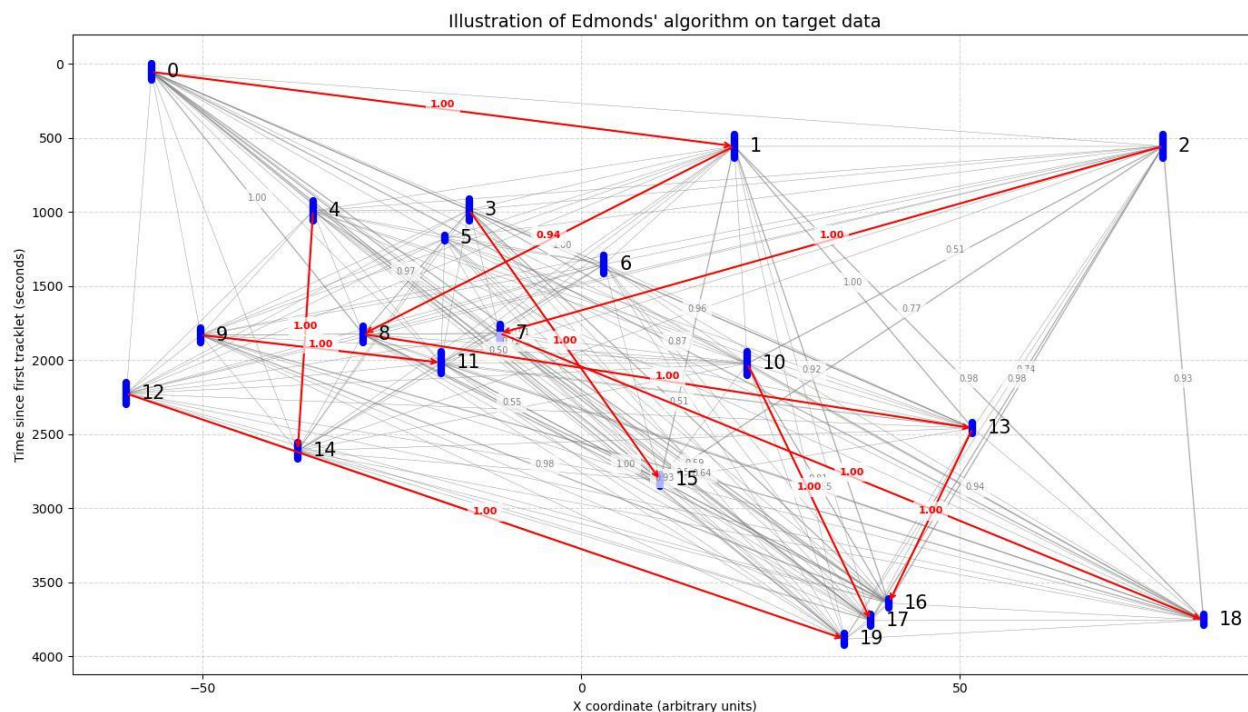
The target set reveals how well the models generalize to completely new observations. All three classifiers achieve perfect Recall (1.0), meaning that no true tracklet pair was missed. But Precision drops significantly compared to the test set. LightGBM suffers the most, producing 37 false positives and a very low Precision (0.327), indicating it is heavily overfitting to the training data distribution. Best trade-off: Random Forest and Decision Tree perform similarly regarding Precision (~0.47–0.48) and false positives (19–20). However, Random Forest shows a vastly superior AUC-PR (0.936 vs 0.713 for DT). This indicates that **Random Forest** ranks pairs much more reliably, making it **more preferable for practical application**. Despite these initial false associations, the subsequent Global Chain Assembly step successfully eliminates inconsistencies, allowing all models to reconstruct the correct tracklet chains.

STEP 4: GLOBAL CHAIN ASSEMBLY (*MAXIMUM WEIGHT MATCHING*)

The Problem: After obtaining pairwise probabilities p_{AB} , we must link multiple tracklets belonging to the same object into continuous chains without contradictions.

The Graph Approach: We construct a **weighted bipartite graph**. Vertices represent tracklet "ends" and "starts". Edges are created for pairs satisfying:

- $p_{AB} \geq 0.5$;
- No temporal overlap (end of A precedes start of B).



The Algorithm: The optimal non-overlapping set of chains is found by solving the **Maximum Weight Matching** problem using **Edmonds' algorithm**. This guarantees each tracklet has at most one predecessor and one successor.

STEP 4: GLOBAL CHAIN ASSEMBLY (RESULTS)

Target set (20 tracklets, 7 chains, 2 singles): All three models successfully reconstructed **100%** of the chains without fragmentation or false merges.

Full training dataset (840 tracklets, 168 chains, 477 singles):

Correct reconstruction:

- RF & LightGBM reconstructed **166/168** chains (98.8%),
- DT reconstructed **165/168** (98.2%).

False merges: RF (4), LightGBM (6), DT (11).

Fragmented chains: RF (2), DT & LightGBM (0).

Conclusion: Random Forest demonstrates the optimal trade-off: high reconstruction accuracy with the fewest false merges, making it the best choice for practical debris chain assembly.

CONCLUSION

- This study shows that approximation residuals that characterize trajectory smoothness and geometric criteria based on apparent motion parameters provide effective discrimination for tracklet association.
- The proposed approach requires no preliminary orbit determination, making it computationally efficient and suitable for real-time applications in space surveillance and fragmentation monitoring.
- Future research will focus on analyzing alternative feature combinations to improve the accuracy of tracklet classification and final chain reconstruction.

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THANK YOU
FOR YOUR ATTENTION!