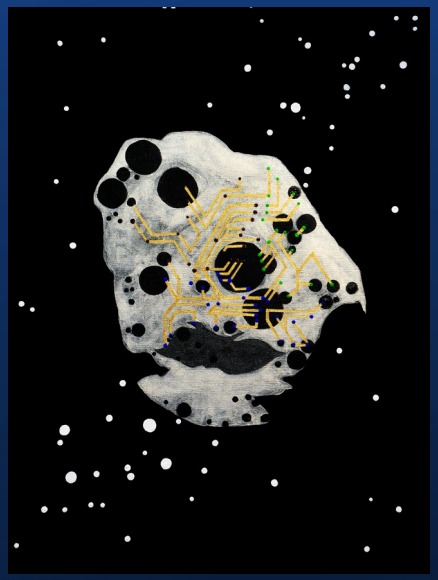
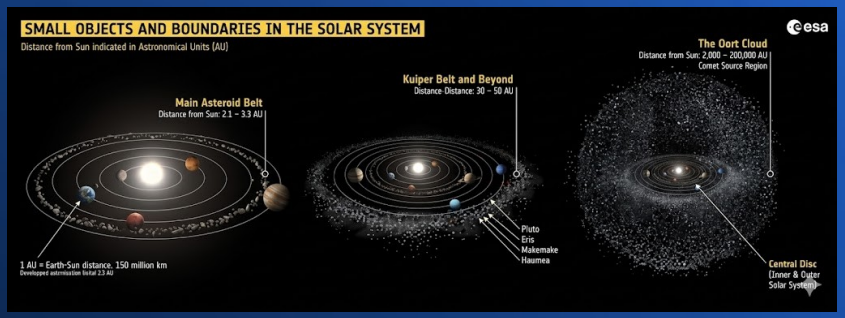
Artificial Intelligence and Machine Learning in Planetary Science

Opportunities and challenges in the Rubin era



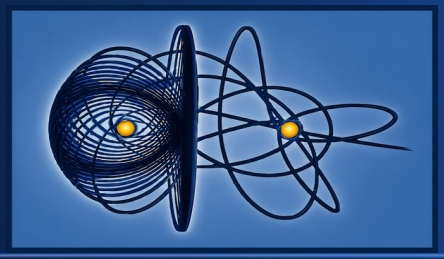




Here's to the ones who dream,

foolish as they may seem

(La La Land, Audition (The Fools Who Dream))



GRUPO DE DINÂMICA ORBITAL & PLANETOLOGIA
DOP

ASB
Machine-learning Applied to Small Bodies

Gaia and the Precision Revolution in Asteroid Dynamics



- Gaia DR3: **>150,000** Solar System objects.
- Unprecedented precision in asteroid astrometry.

Gaia and the Precision Revolution in Asteroid Dynamics

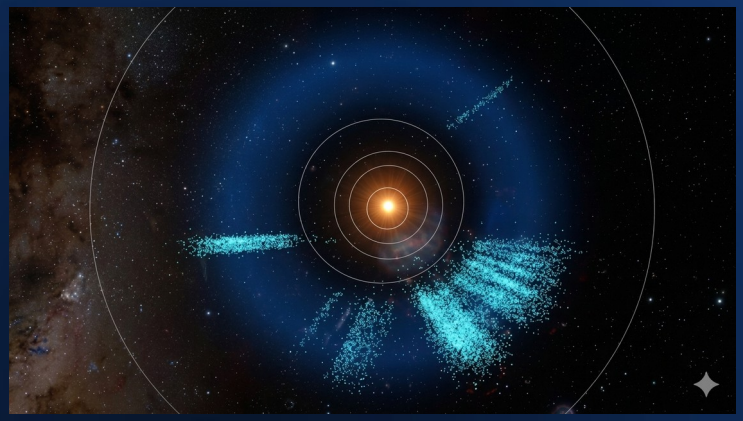


- Gaia DR3: **>150,000** Solar System objects.
- Unprecedented precision in asteroid astrometry.
- Millions of observations constrain orbits, families, and resonances.
- Precision at scale creates new opportunities for AI/ML.

Precision astronomy demands scalable analysis

Rubin Observatory and the Data Revolution

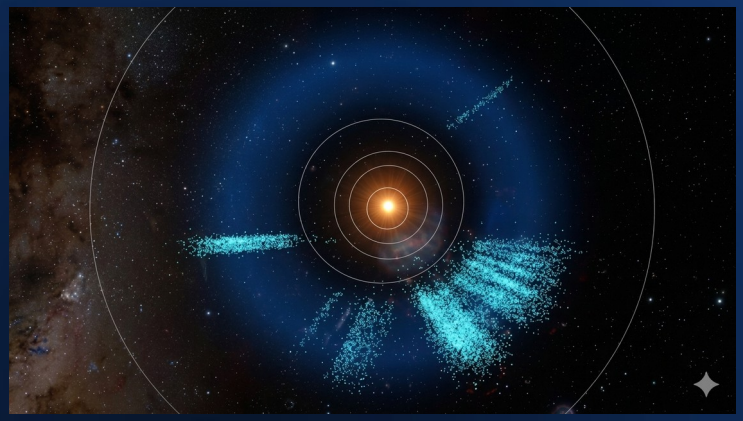




- Rubin/LSST will transform Solar System discovery.
- Millions of objects require automated analysis.

Rubin Observatory and the Data Revolution

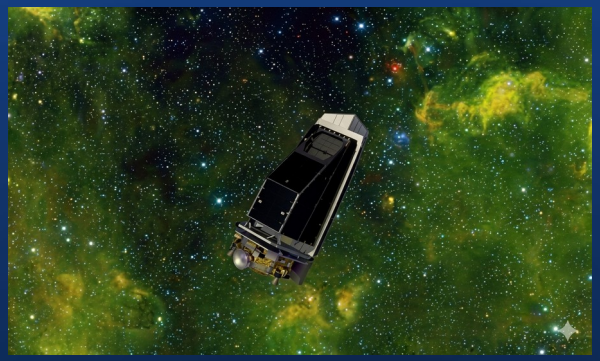




- Rubin/LSST will transform Solar System discovery.
- Millions of objects require automated analysis.
- Classical dynamical workflows cannot scale efficiently.

Rubin turns precision astronomy into a problem of scale

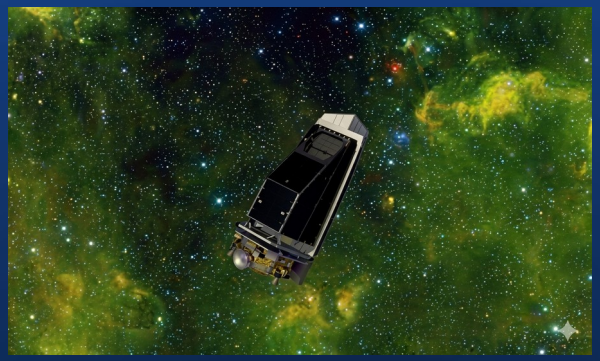
The Survey Revolution in Planetary Astronomy





- NEO Surveyor → infrared planetary defense.
- Roman → deep wide-field surveys.

The Survey Revolution in Planetary Astronomy







- NEO Surveyor → infrared planetary defense.
- Roman → deep wide-field surveys.
- ZTF → real-time transient discovery.

Discovery is no longer the bottleneck — interpretation is

From Celestial Mechanics to Machine Learning

1. Dynamics

The physical system



N-body dynamics

$$\dot{\mathbf{x}} = f(\mathbf{x}, \mu)$$

state $\mathbf{x}$, parameters μ

2. Representation

Dynamical descriptors

$$\mathbf{z} = \Phi[\mathbf{x}(t)]$$

- Proper elements
- Chaos indicators
- Resonant angles
- Images / Light curves
- Frequencies
- Other representations

3. ML Inference

Scalable prediction

$$\hat{\mathbf{y}} = M(\mathbf{z})$$

- Classification
- Clustering
- Regression
- Anomaly detection
- Other tasks

From orbits to insights: *physics* → *representation* → *machine learning* → *understanding*

Takeaway: *ML does not replace the dynamics — it learns from dynamical representations.*

WHAT ARE AI, MACHINE LEARNING, DEEP LEARNING, AND LLMs?

AI is a family of methods, not a single technology



Artificial Intelligence (AI)

Systems designed to solve complex tasks that normally require human intelligence

The broad goal: perception, reasoning, planning, decision-making, and more.



Machine Learning (ML)

Algorithms that learn patterns from data to make predictions or decisions

Learns from data: finds patterns and makes predictions without being explicitly programmed.



Deep Learning (DL)

Uses deep neural networks with many layers to model complex, high-dimensional data (images, time series, sequences, etc.)

Powerful function approximators: excels on large, complex datasets and unstructured inputs.



Modern Foundation Models: LLMs and Multimodal Models

Large-scale models (e.g., LLMs) trained on massive data. Applicable to language, code, and increasingly multimodal scientific data.

Built on deep learning: optimized for broad capability and transfer to many tasks (language, code, images, and more).

These methods overlap and complement each other.
We choose the right tool for the scientific question.

AI is a family of methods, not a single technology

A Brief History of Artificial Intelligence

1956



Birth of Artificial Intelligence

1997



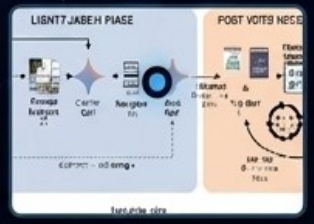
AI defeats a world champion

2012



Deep learning enters the mainstream

2024



Autonomous AI assistants

2022



Generative AI

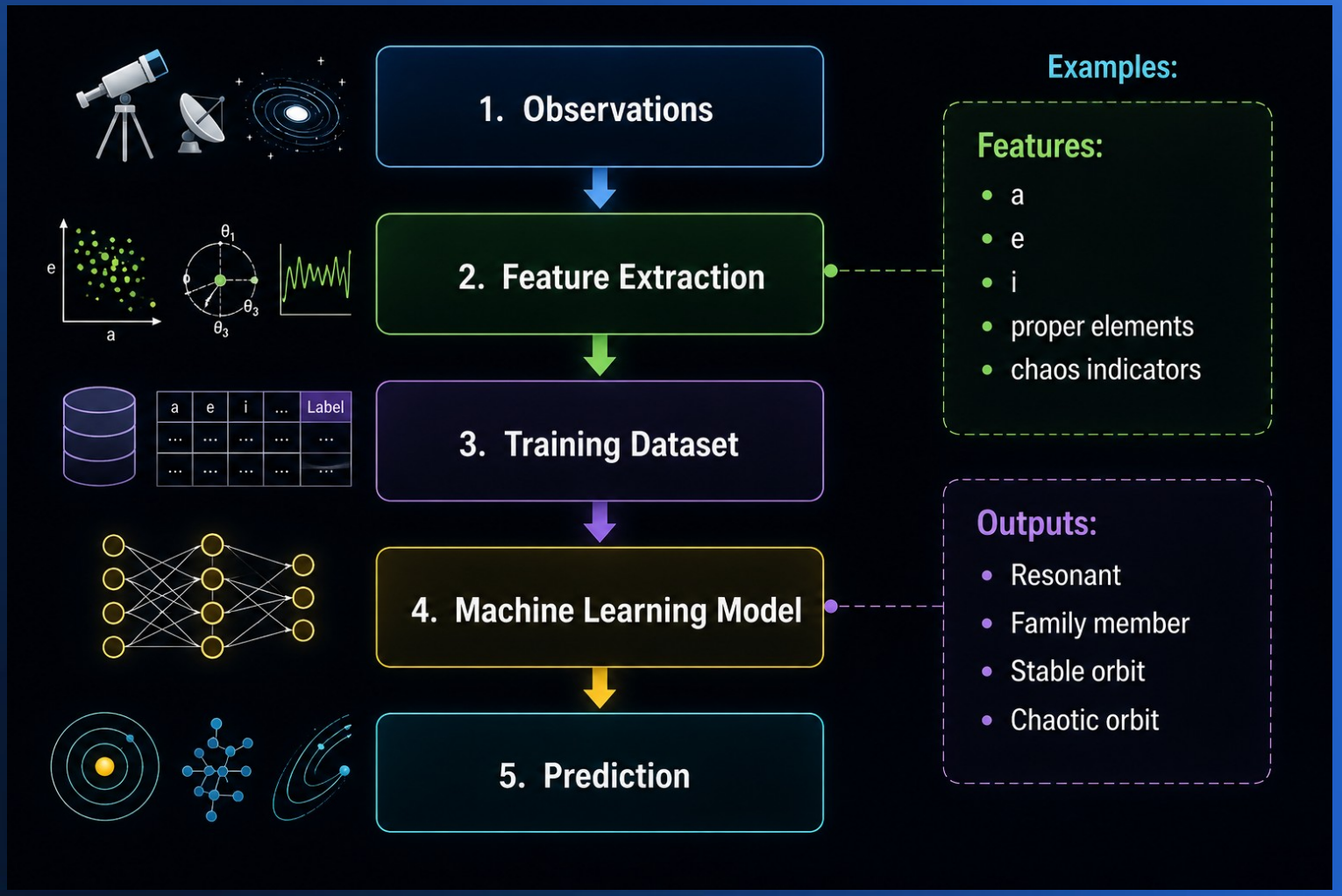
2025+



AI-assisted science

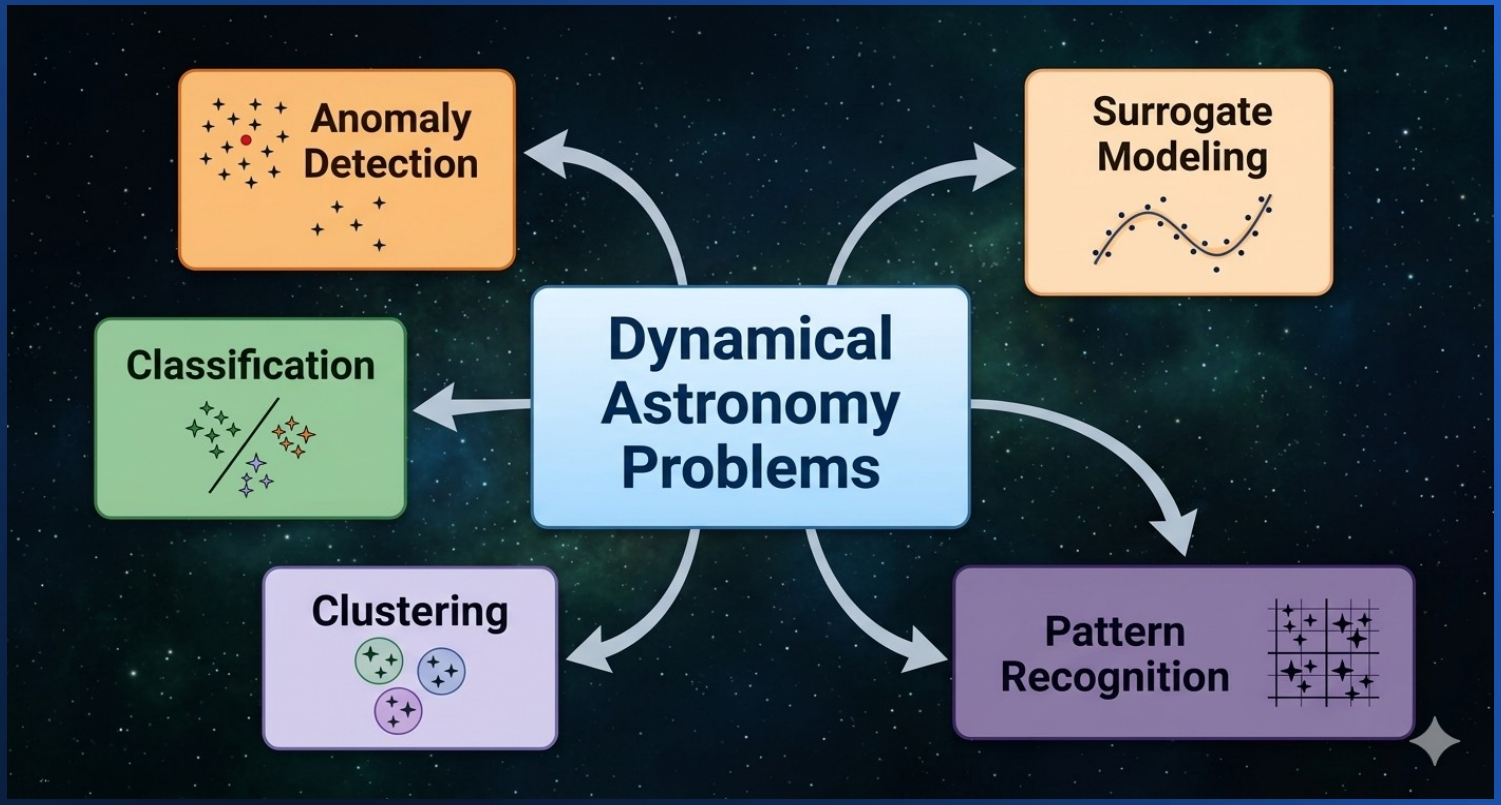
Recent breakthroughs transformed AI from a niche technology into a mainstream scientific

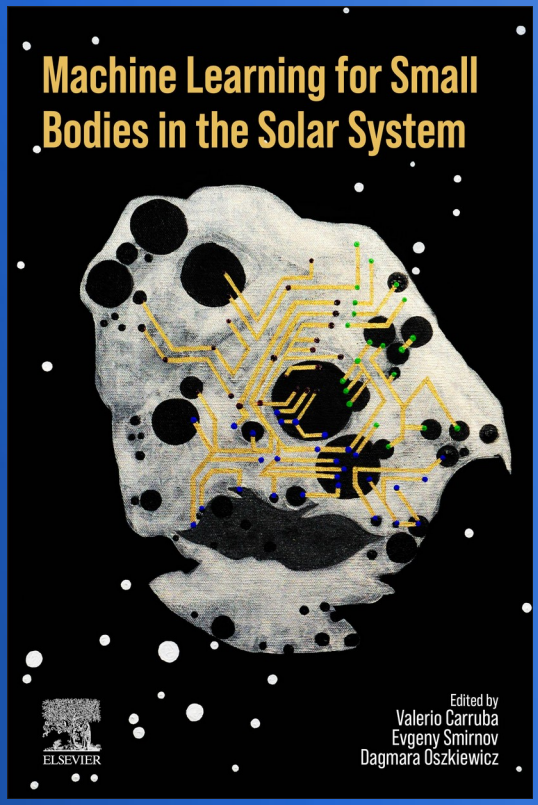
A Typical Machine-Learning Workflow in Celestial Mechanics



ML performance depends critically on the dynamical representation and training

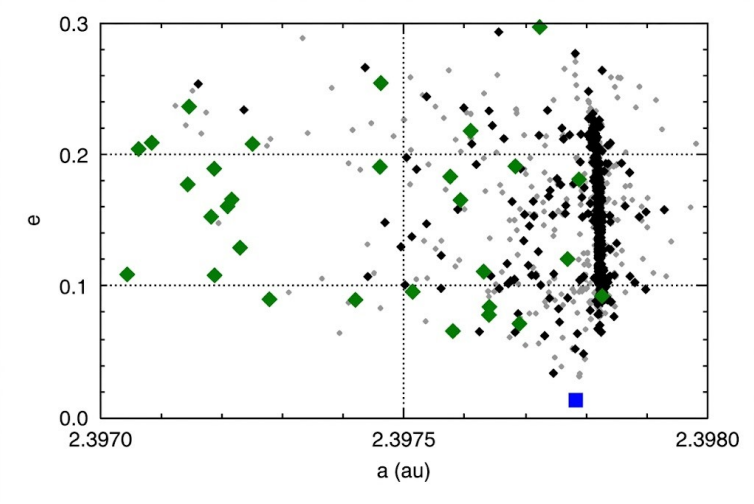
Where ML Fits in Dynamical Astronomy





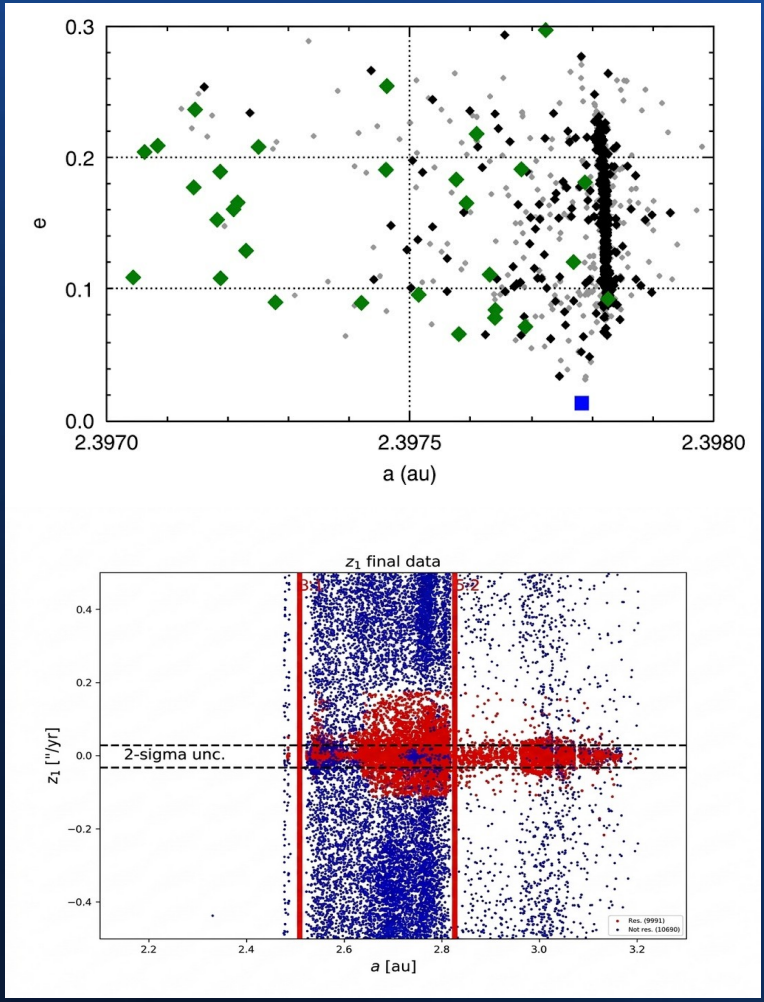
Different scientific questions require different ML strategies

Classical ML for Resonance Classification



- Resonance identification traditionally requires expensive integrations.
- KNN and GBoost rapidly classify resonant populations.

Classical ML for Resonance Classification

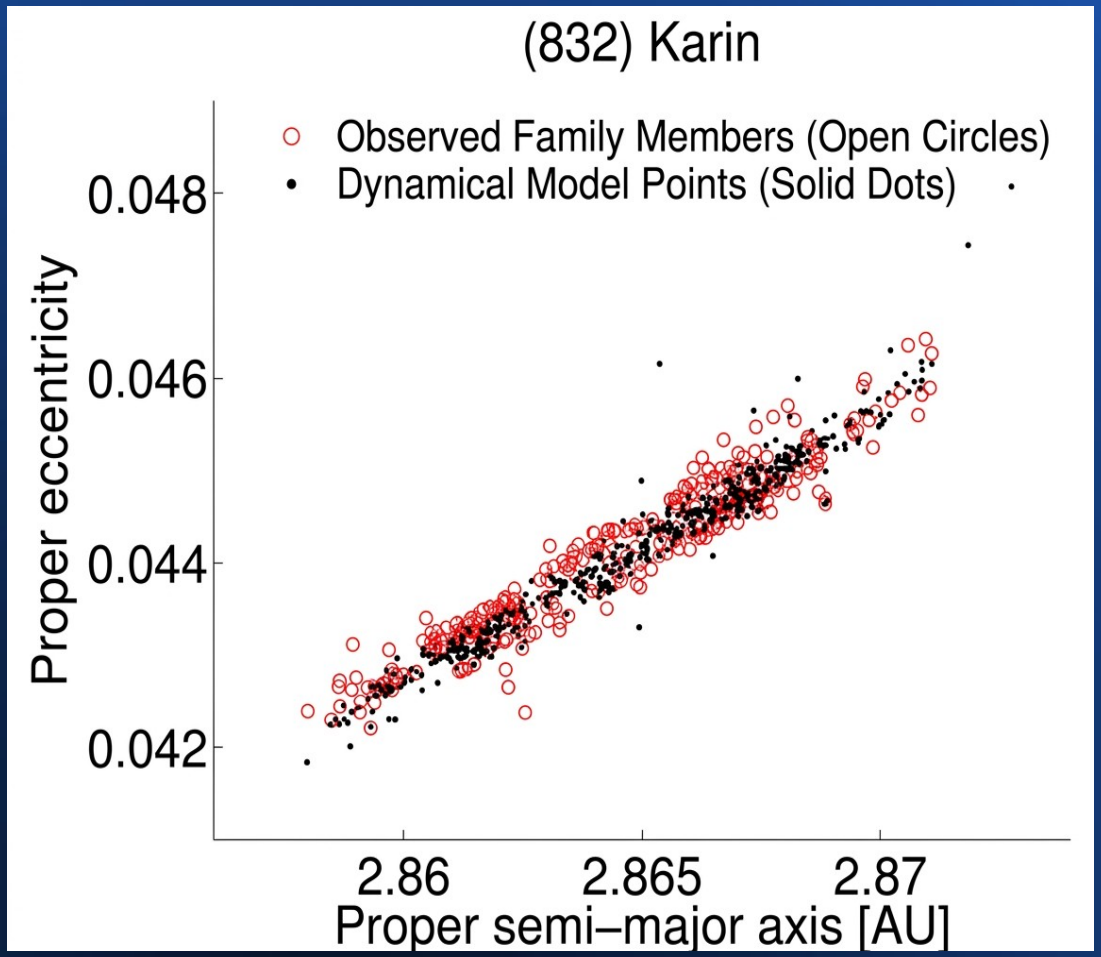


- Resonance identification traditionally requires expensive integrations.
- KNN and GBoost rapidly classify resonant populations.
- Computation time drops from days to seconds.
- Genetic algorithms optimize the classification workflow.

- Smirnov and Markov (2017), Carruba et al. (2021)

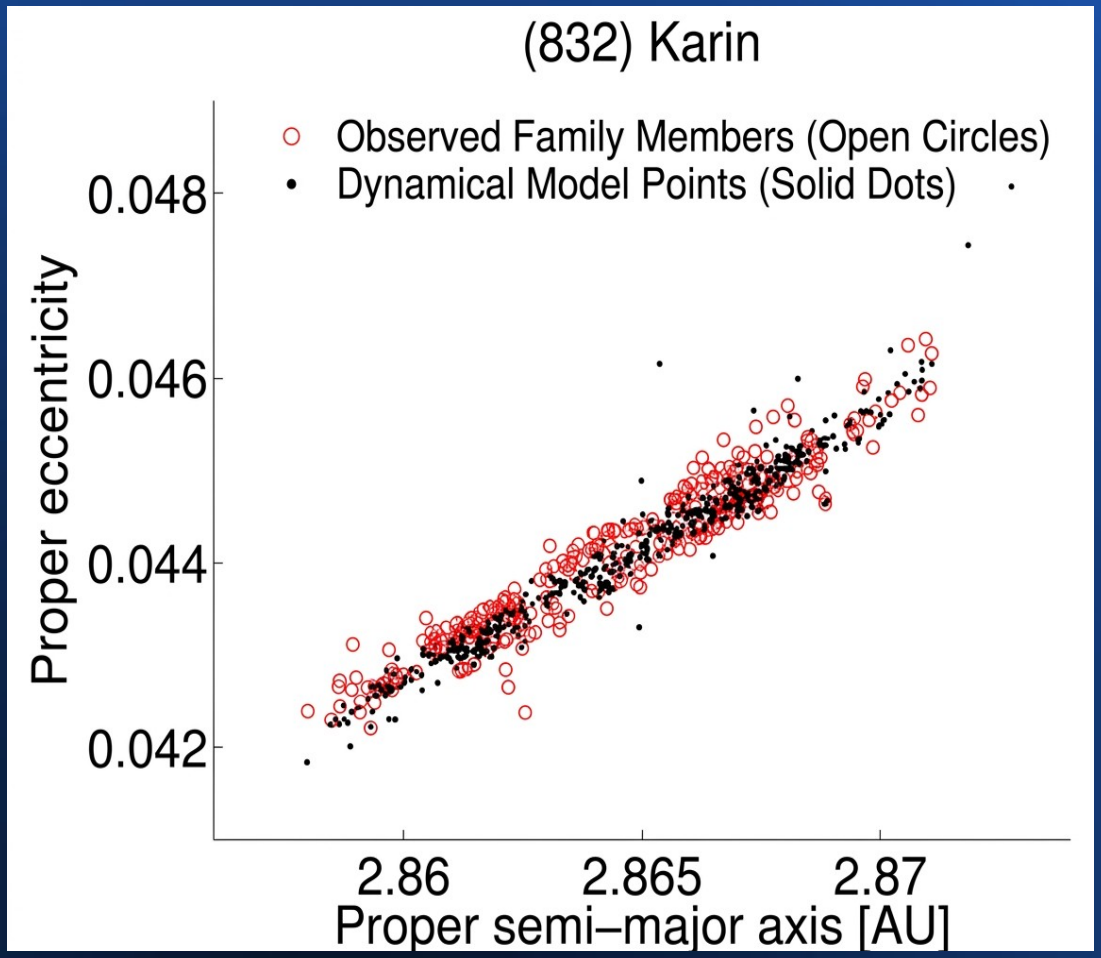
Resonance classification became one of the first major ML successes in dynamical astronomy

Classical ML for Asteroid Families



- Asteroid families form clusters in proper-element space (*a*,*e*,sin(*i*)).
- ML classifiers identify new members from known orbital distributions.

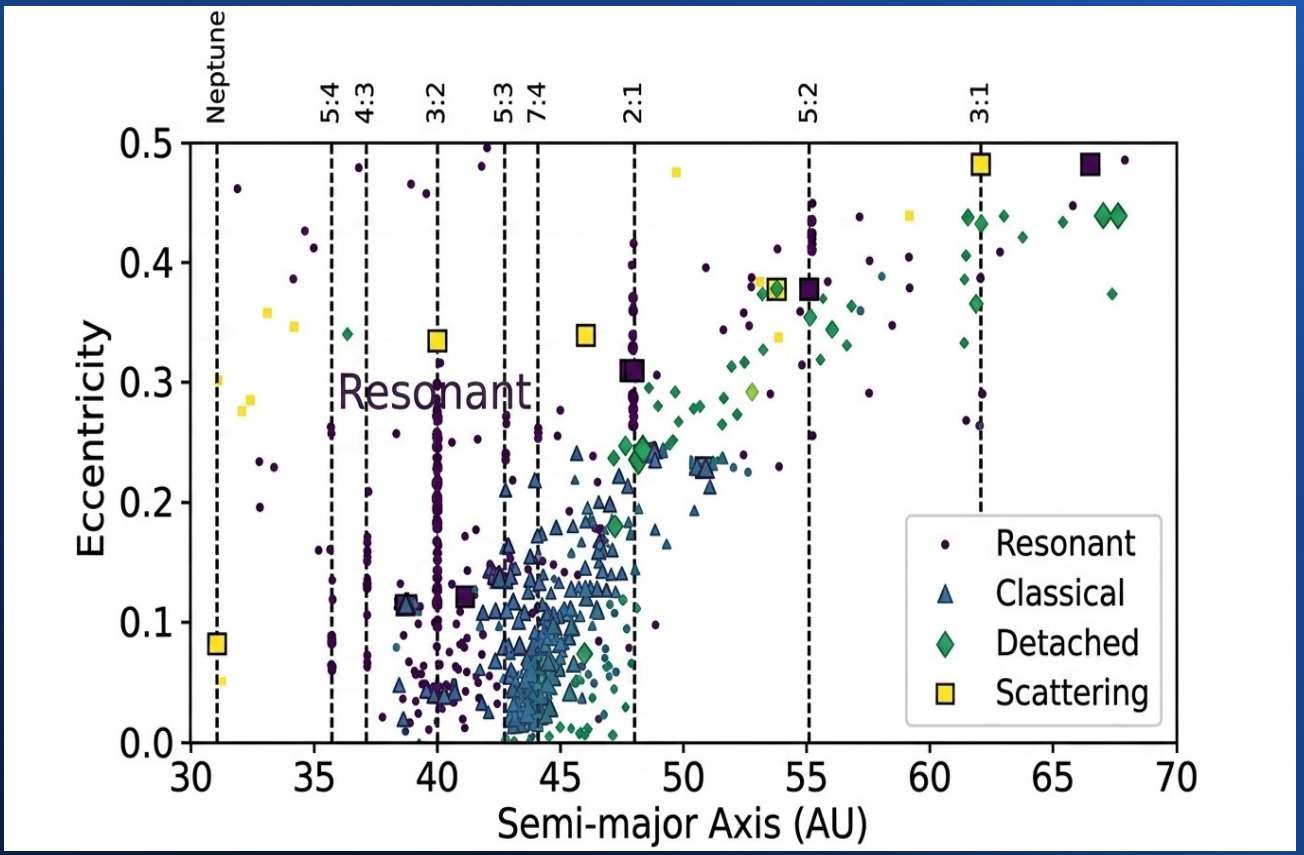
Classical ML for Asteroid Families



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- ML classifiers identify new members from known orbital distributions.
- ExtraTrees recovered up to 97% of HCM family members.
- Carruba et al. (2020)

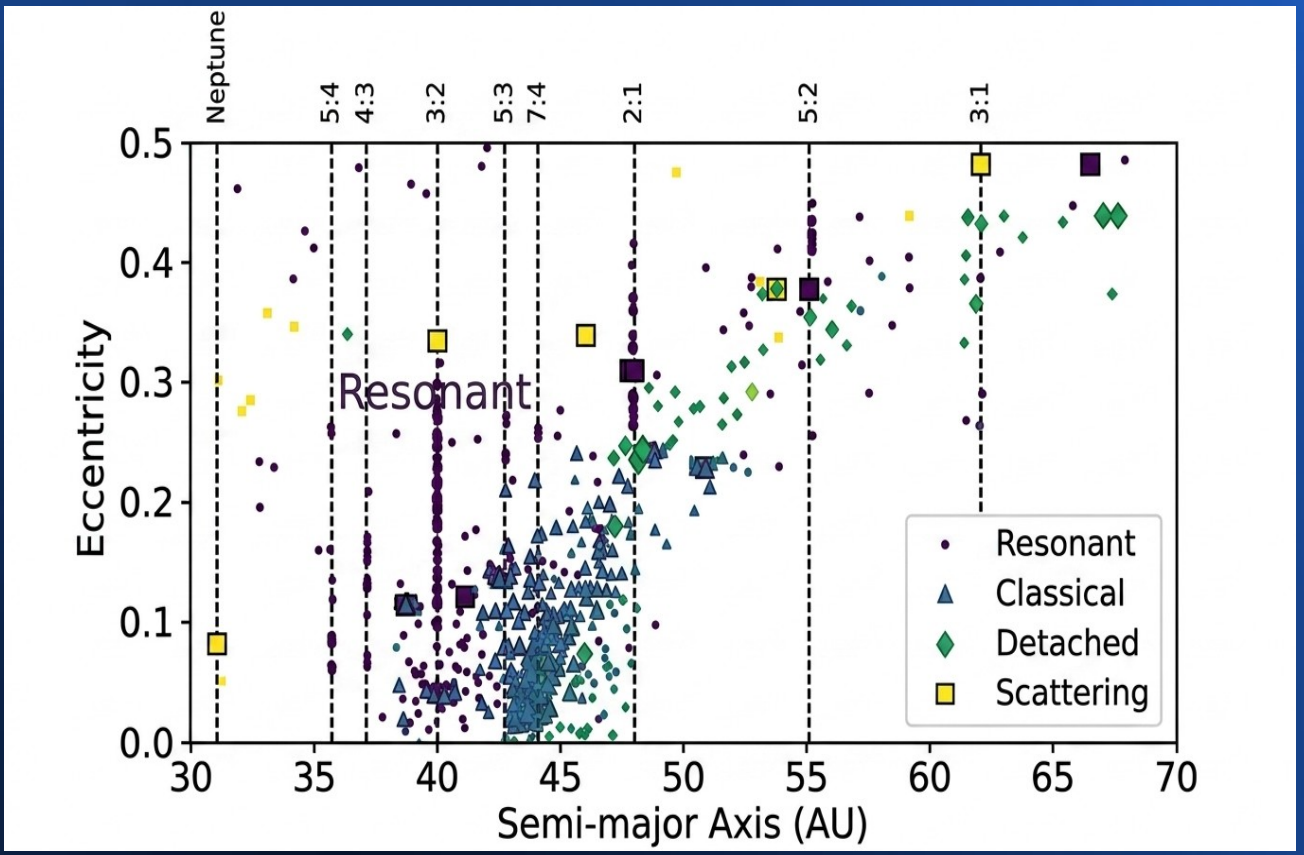
Classical ML enables fast, automated recovery of asteroid-family

Machine Learning Classification of Kuiper Belt Populations



- TNO classification traditionally requires numerical integrations and human inspection.
- Gradient Boosting uses features from short numerical integrations to classify four dynamical populations.

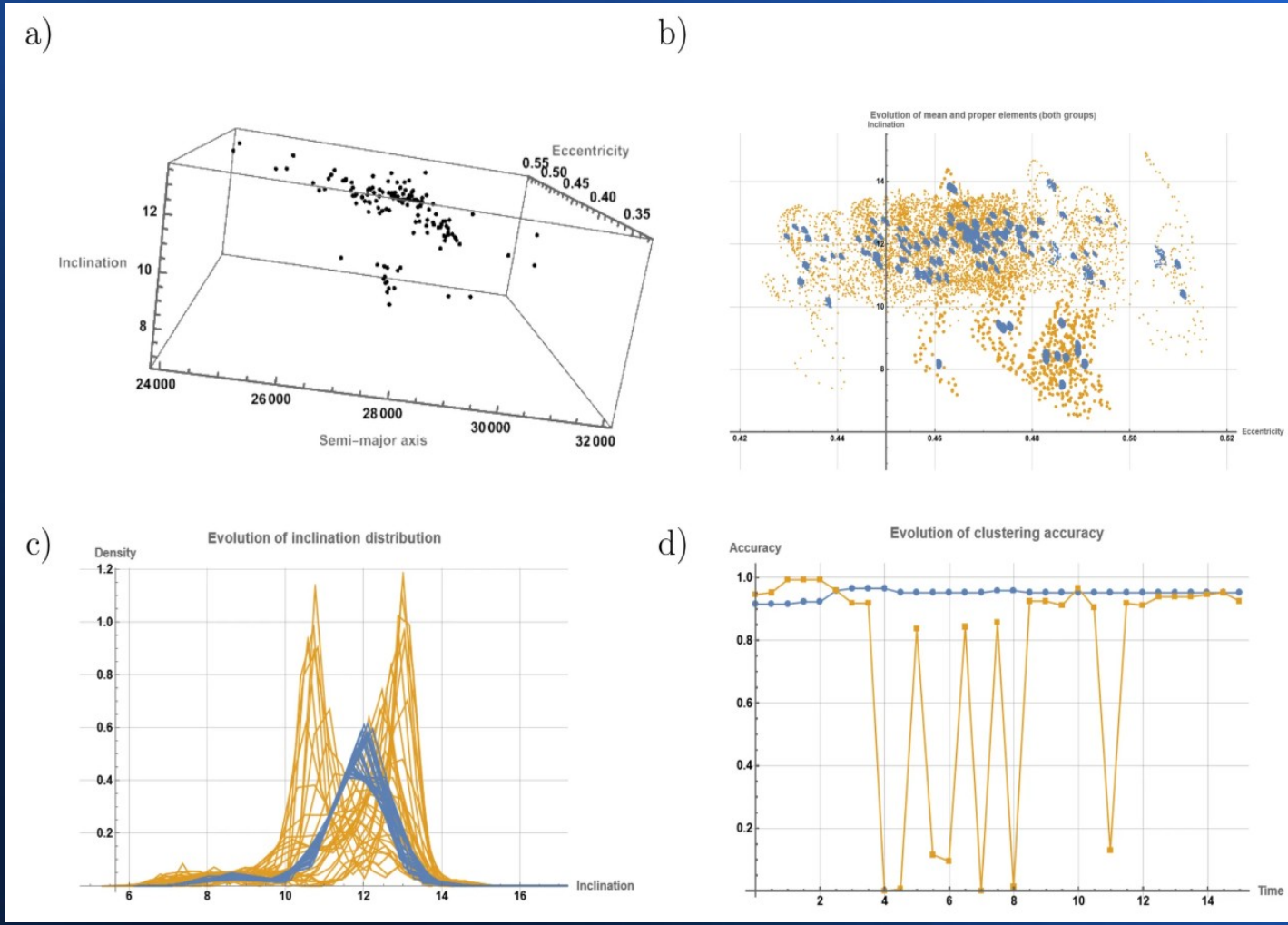
Machine Learning Classification of Kuiper Belt Populations



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- Gradient Boosting uses features from short numerical integrations to classify four dynamical populations.
- >97% accuracy for securely classified KBOs; major savings in computation and manual effort.
- Smullen and Volk (2020)

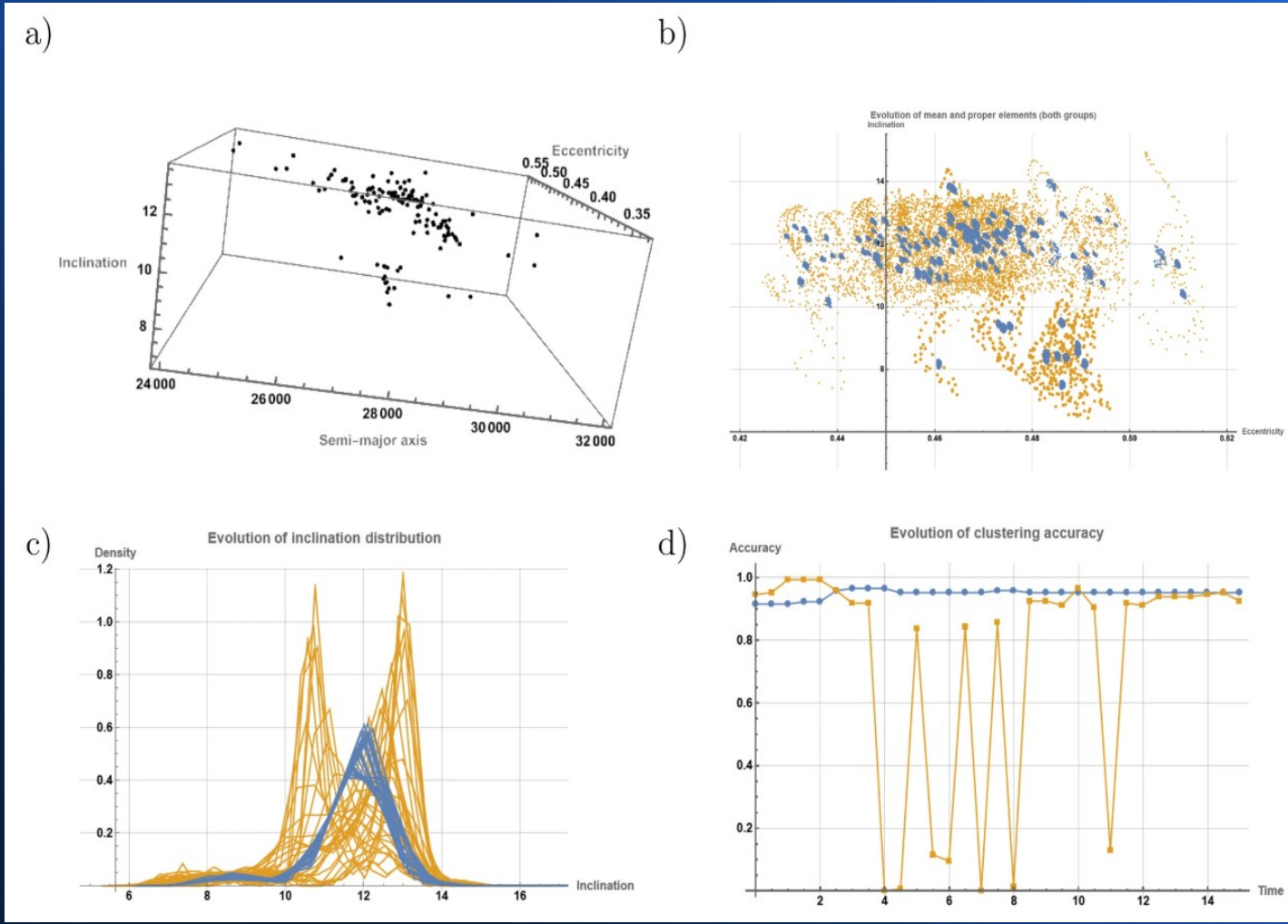
Dynamically informed ML can reproduce expensive human classification at survey scale

Dynamics-Informed ML: Proper Elements for Space Debris



- Perturbation theory transforms orbital elements into nearly invariant proper elements.
- Proper-element space preserves the dynamical fingerprint of fragments from break-up events.

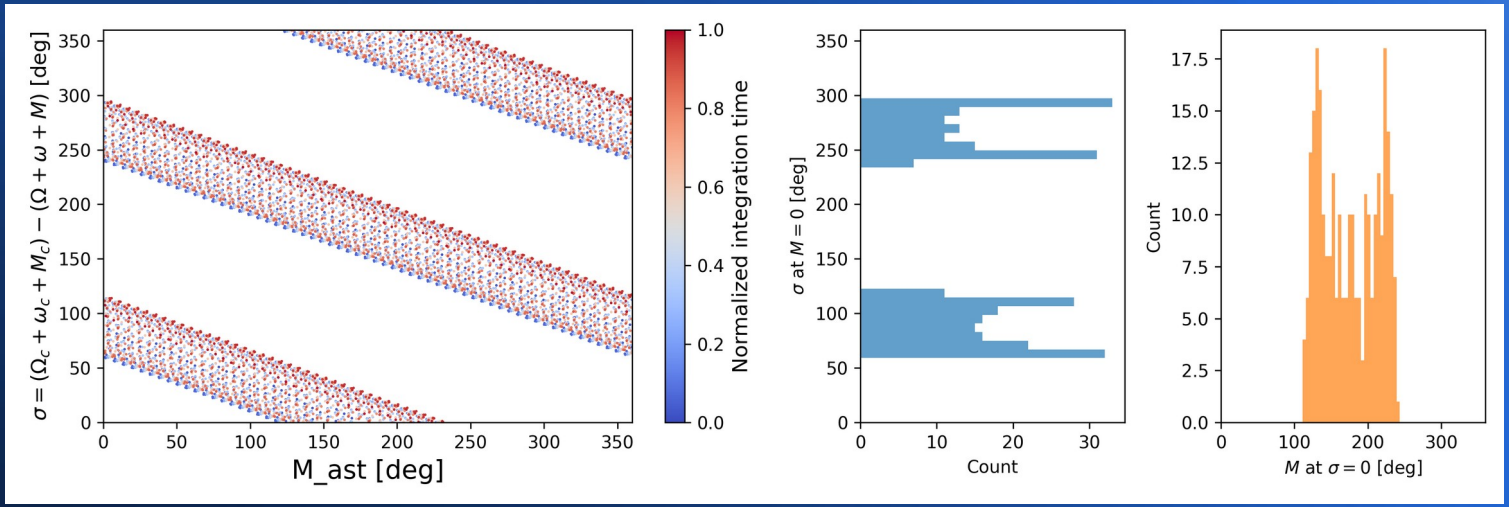
Dynamics-Informed ML: Proper Elements for Space Debris



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- DBSCAN and supervised classifiers can then recover debris groups more reliably.
- Celletti and Vartolomei (2025).

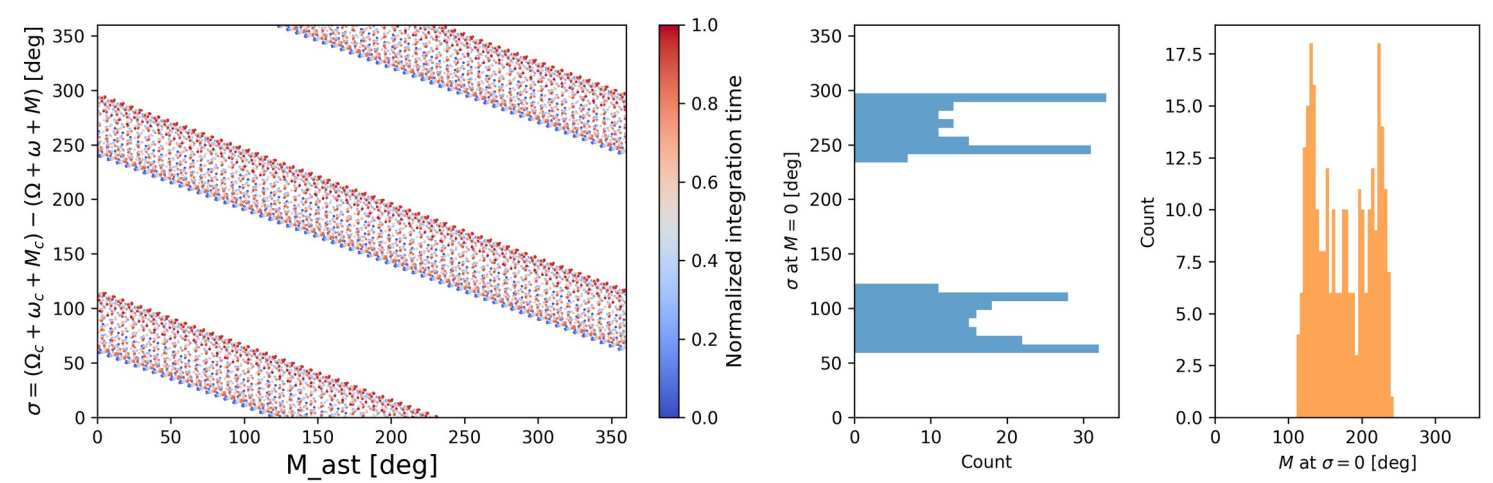
Physics supplies the representation; machine learning reveals the

ML-FAIR: Automated Resonance Identification



- FAIR converts resonance detection into stripe counting in angle–angle space.
- ML-FAIR uses OPTICS + circular KDE to detect stripe intersections automatically.

ML-FAIR: Automated Resonance Identification

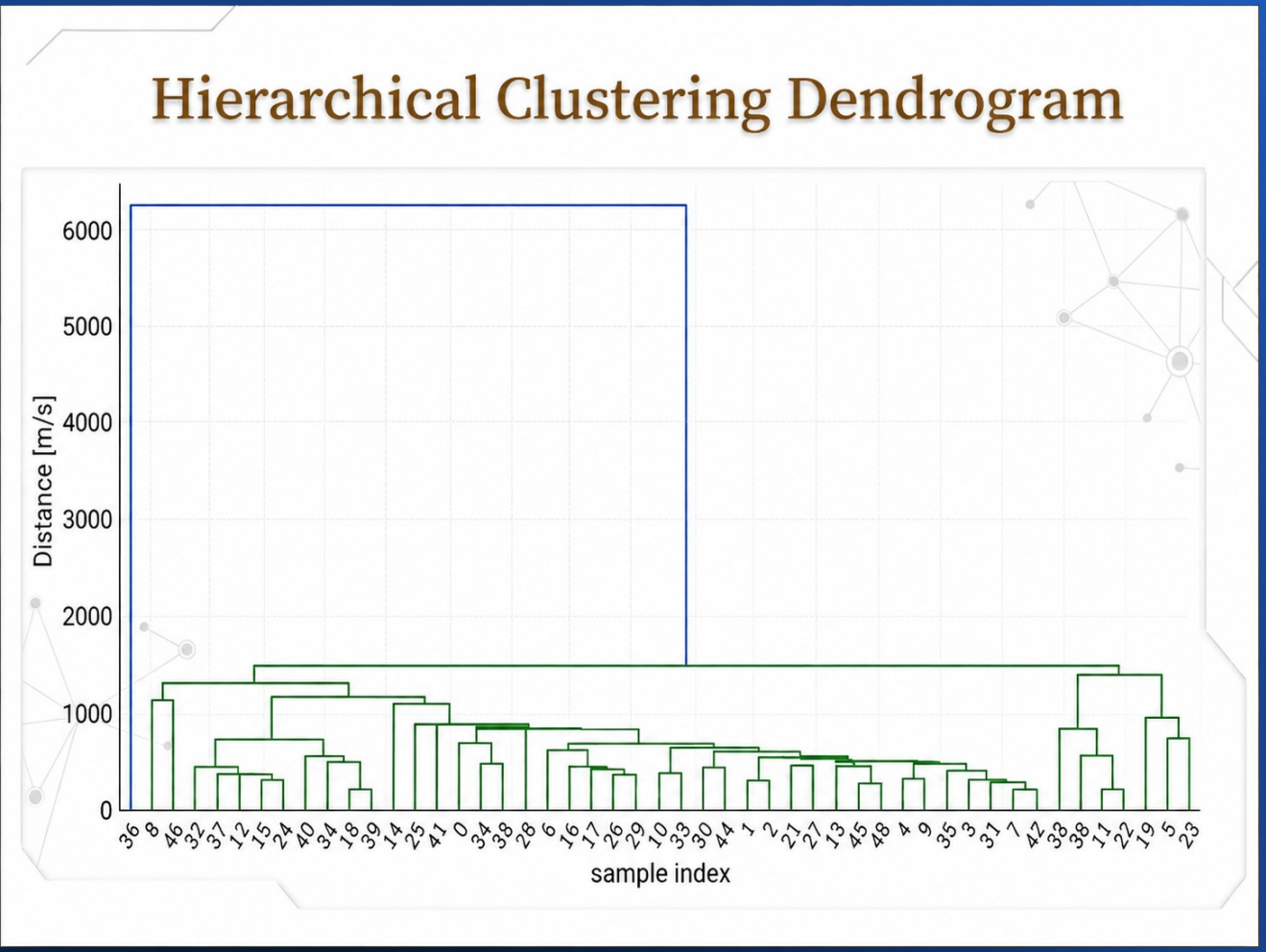


- FAIR converts resonance detection into stripe counting in angle–angle space.
- ML-FAIR uses OPTICS + circular KDE to detect stripe intersections automatically.
- Applied to 2,882 Aten/Atira cases, >85% were screened automatically.
- Good qualitative agreement with long-timescale resonance diagnostics, at much lower analysis cost.

- Carruba et al. (2026)

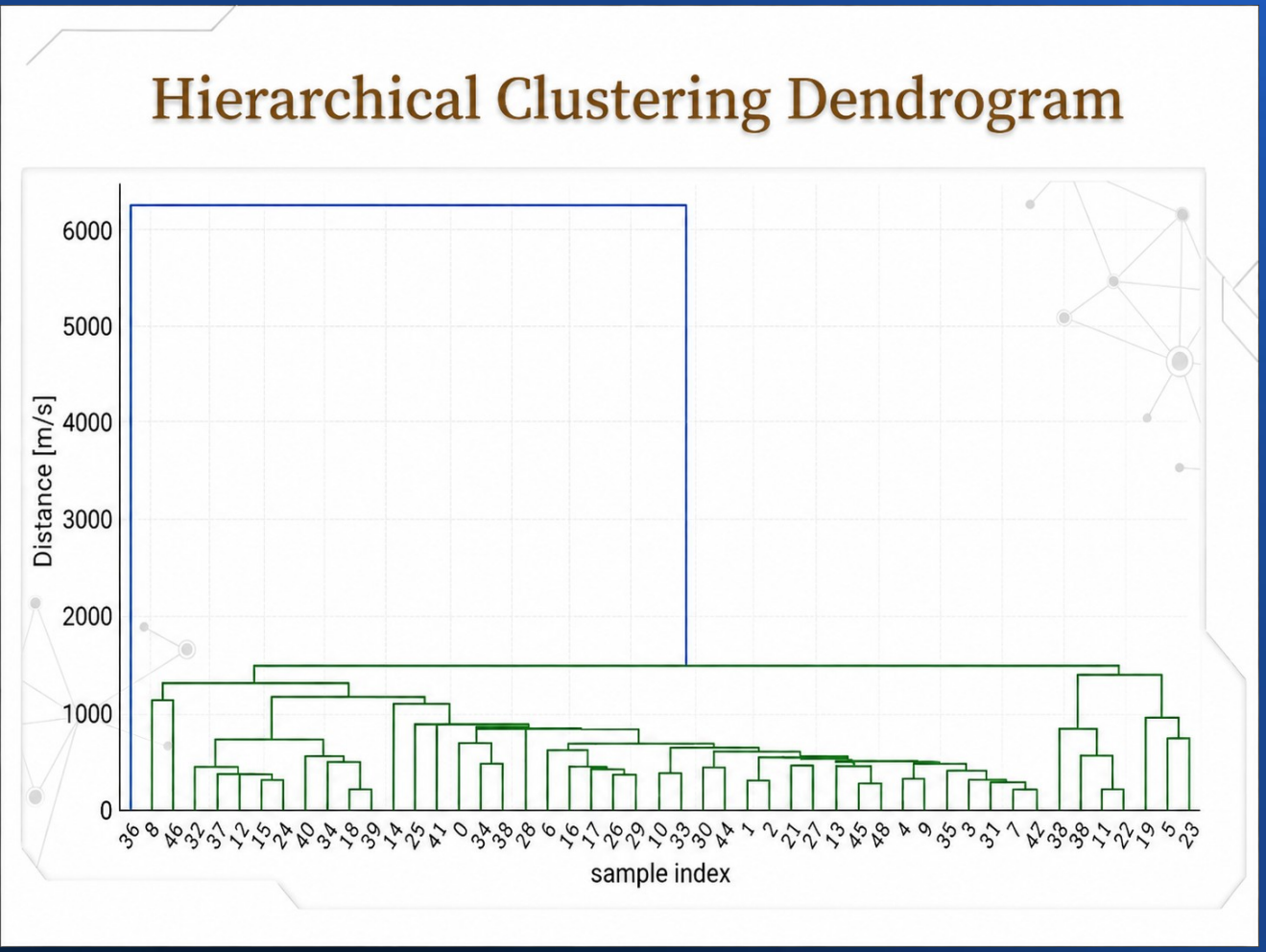
ML-FAIR turns resonance identification into scalable pattern

Machine Learning for Asteroid-Family Discovery



- Six new asteroid families and 13 new dynamical groups identified.
- Large catalogs contain previously unrecognized dynamical structure.

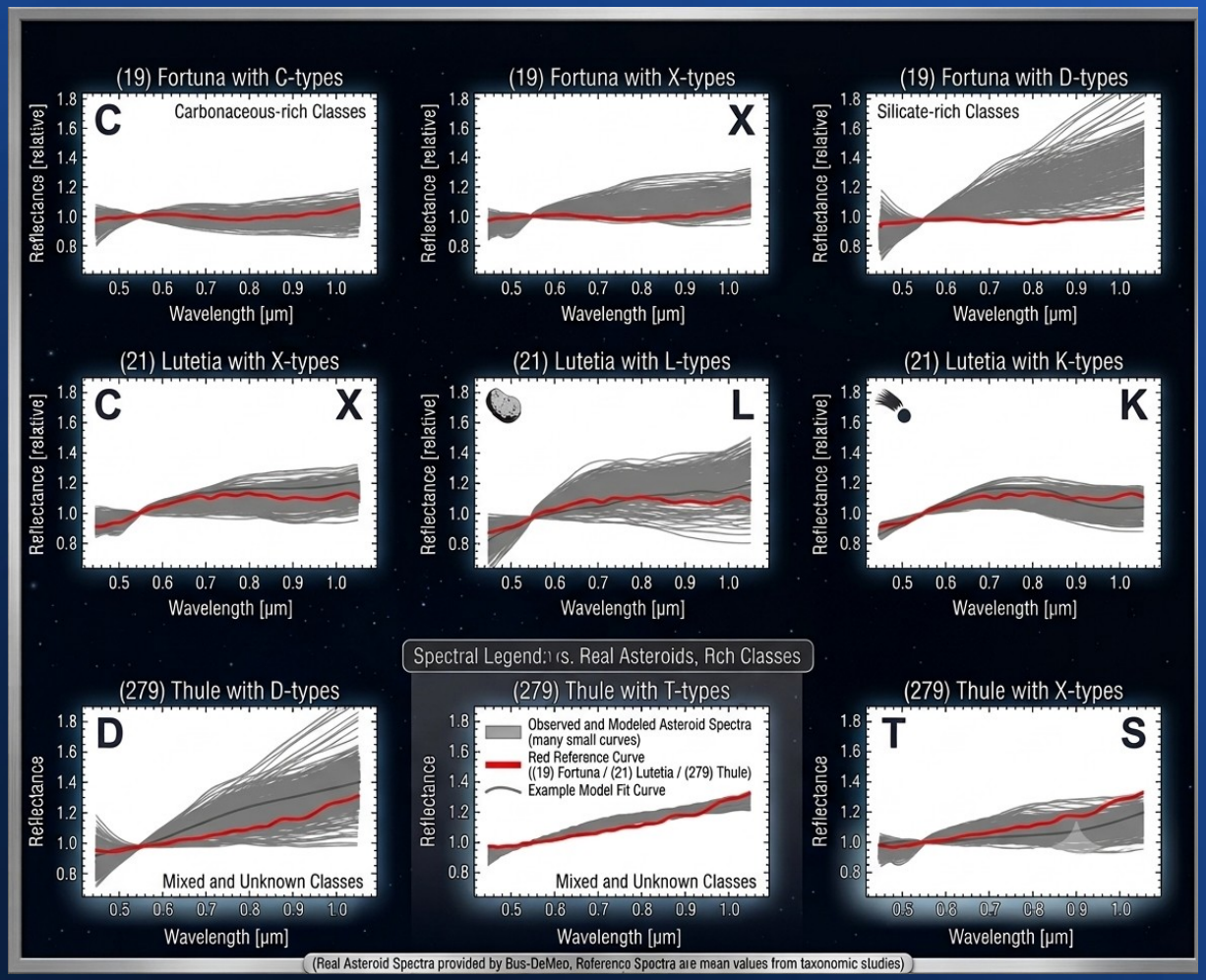
Machine Learning for Asteroid-Family Discovery



- Six new asteroid families and 13 new dynamical groups identified.
- Large catalogs contain previously unrecognized dynamical structure.
- Hierarchical clustering can discover asteroid families automatically.
- Family membership recovered with >89.5% accuracy.
- Carruba et al. (2019)

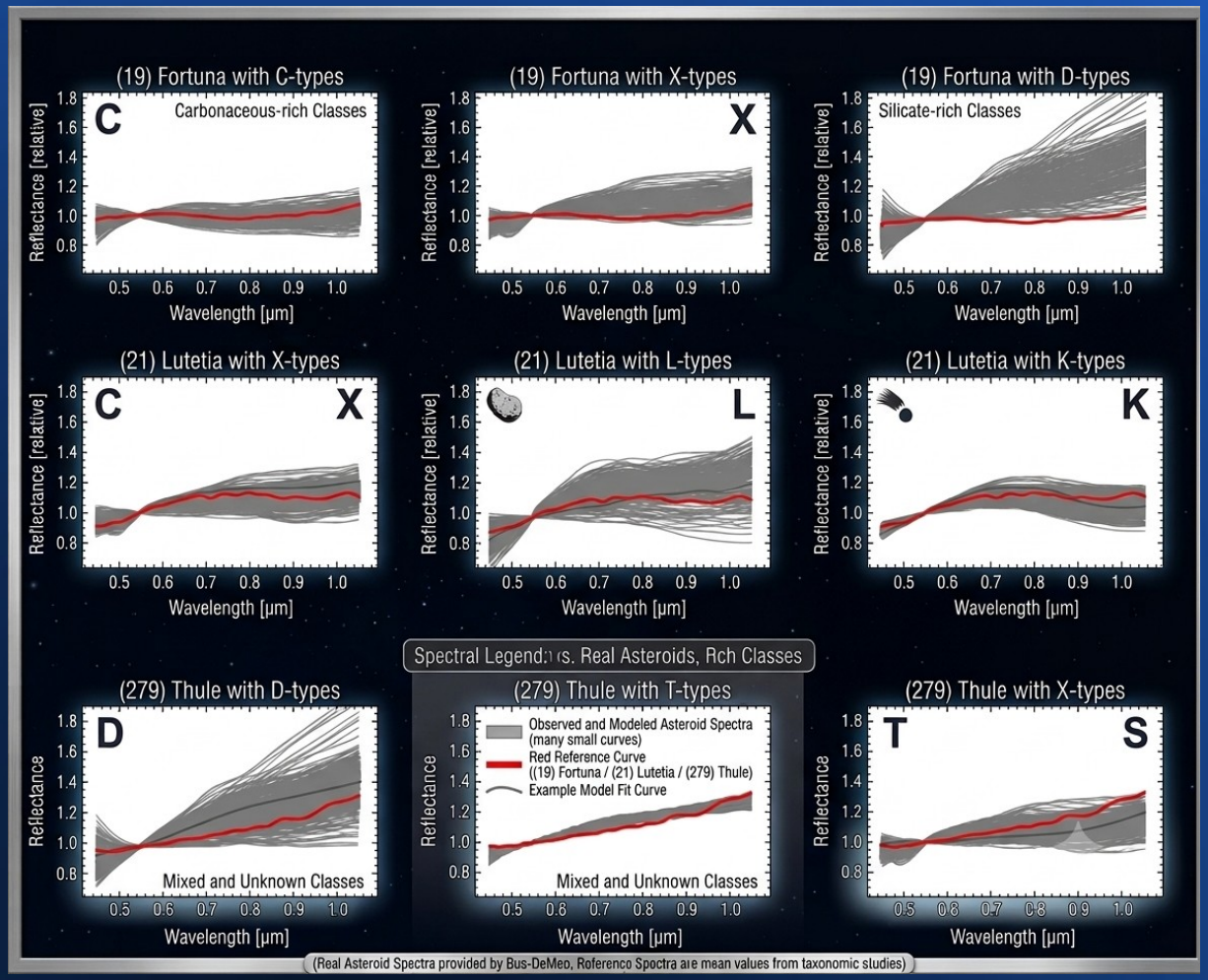
Machine learning turns asteroid-family identification into scalable discovery

Neural Networks for Asteroid Taxonomy



- Neural networks learn mappings from spectra to taxonomic classes.

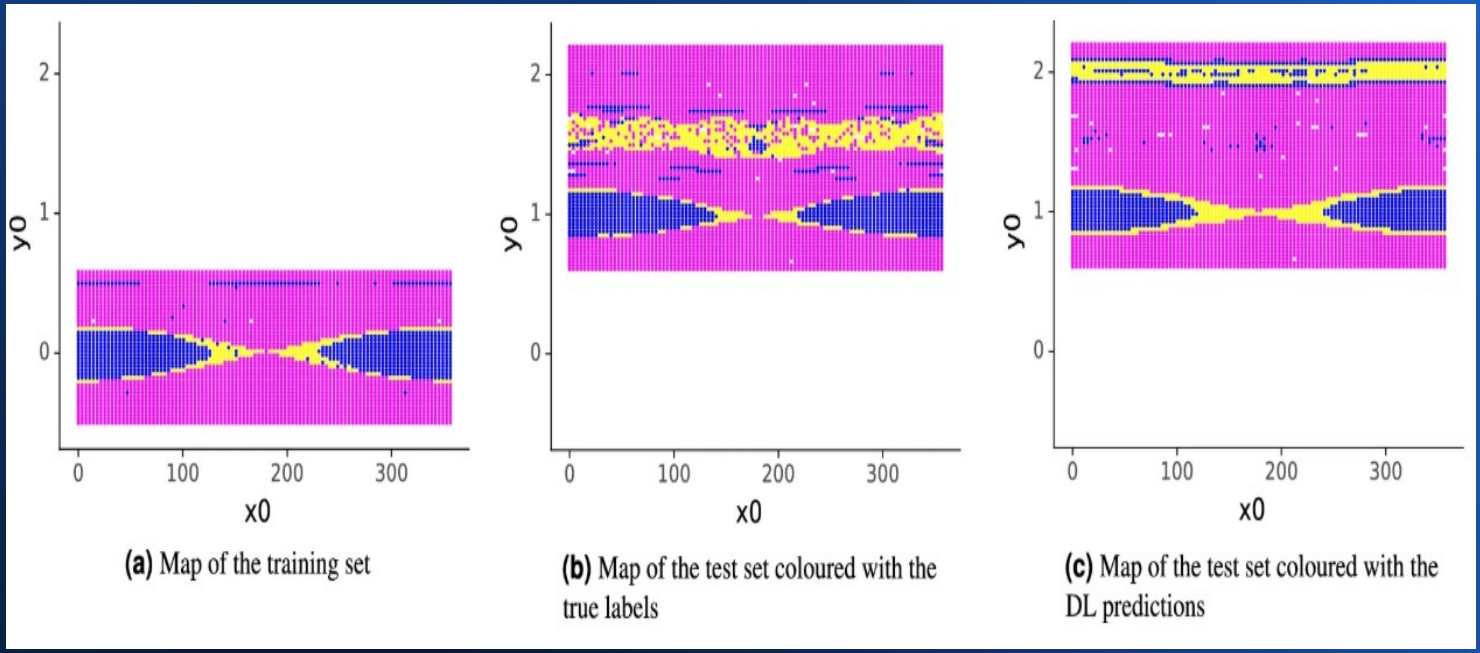
Neural Networks for Asteroid Taxonomy



- Neural networks learn mappings from spectra to taxonomic classes.
- Gaia-like observations can reproduce Bus–DeMeo taxonomy.
- The approach is scalable to large survey datasets.
- Penttilä et al. (2021)

ML can extract physical properties as well as dynamical structure

Deep Learning for Hamiltonian Dynamics



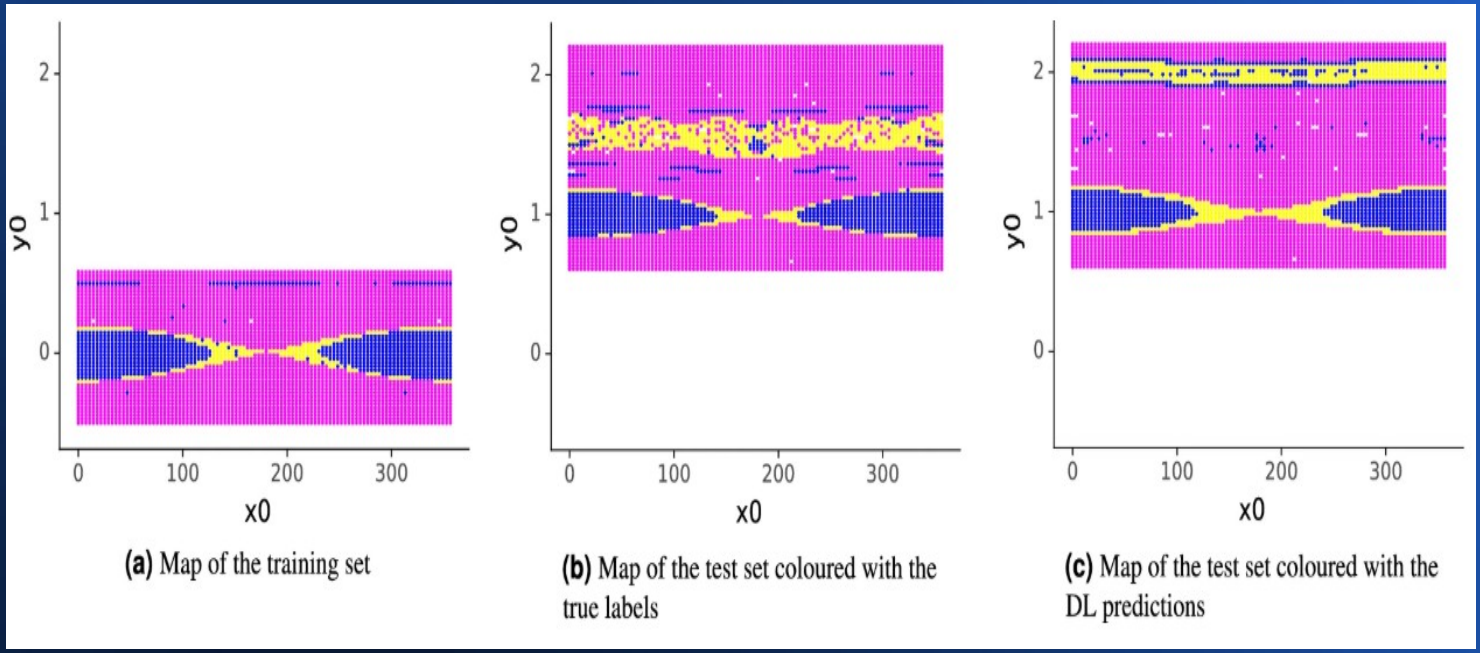
(a) Map of the training set

(b) Map of the test set coloured with the true labels

(c) Map of the test set coloured with the DL predictions

- CNNs classify chaotic, librational, and rotational trajectories directly from time series.
- Training labels are provided by classical dynamical indicators such as FLI and frequency analysis.

Deep Learning for Hamiltonian Dynamics



(a) Map of the training set

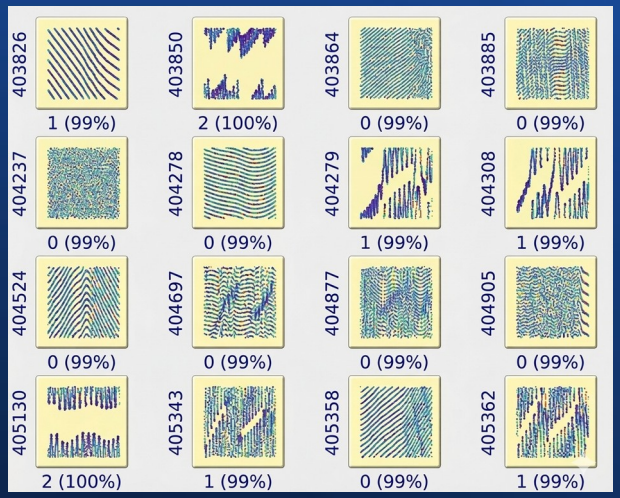
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- CNNs classify chaotic, librational, and rotational trajectories directly from time series.
- Training labels are provided by classical dynamical indicators such as FLI and frequency analysis.
- The method generalizes to related Hamiltonian systems, including the spin–orbit problem.
- Celletti et al. (2022)

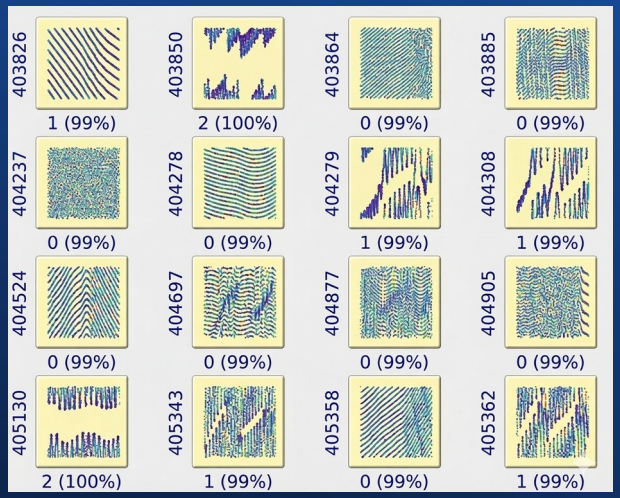
Deep learning can reproduce dynamical classification—but it learns patterns, not the underlying equations

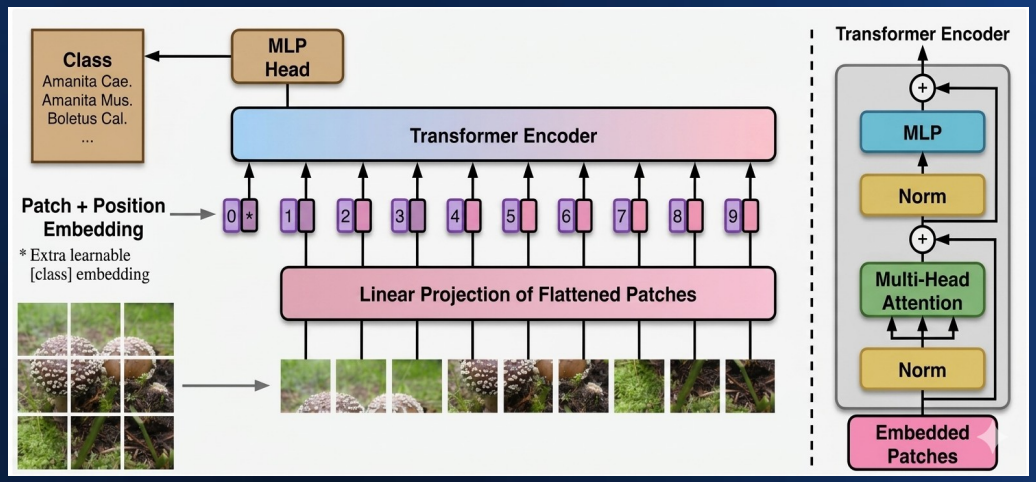
Deep Learning for Dynamical Image Analysis



- Deep neural networks automatically recognize dynamical patterns in resonance images.
- CNN architectures (VGG, Inception, ResNet) classified resonant asteroid populations from time-series images.

Deep Learning for Dynamical Image Analysis



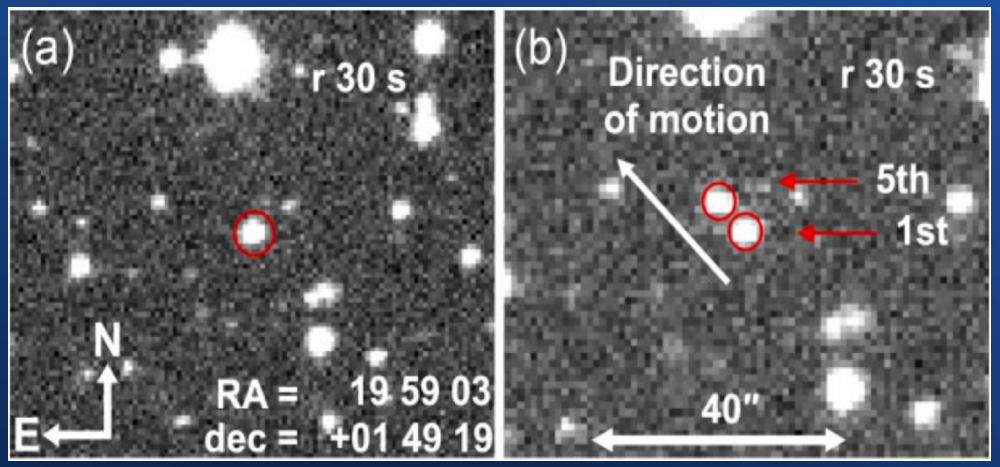


- Deep neural networks automatically recognize dynamical patterns in resonance images.
- CNN architectures (VGG, Inception, ResNet) classified resonant asteroid populations from time-series images.
- Vision Transformers learned dynamical patterns beyond traditional CNN approaches.

- Carruba et al. (2021, 2022, 2024, 2025), Caritá et al. (2024)

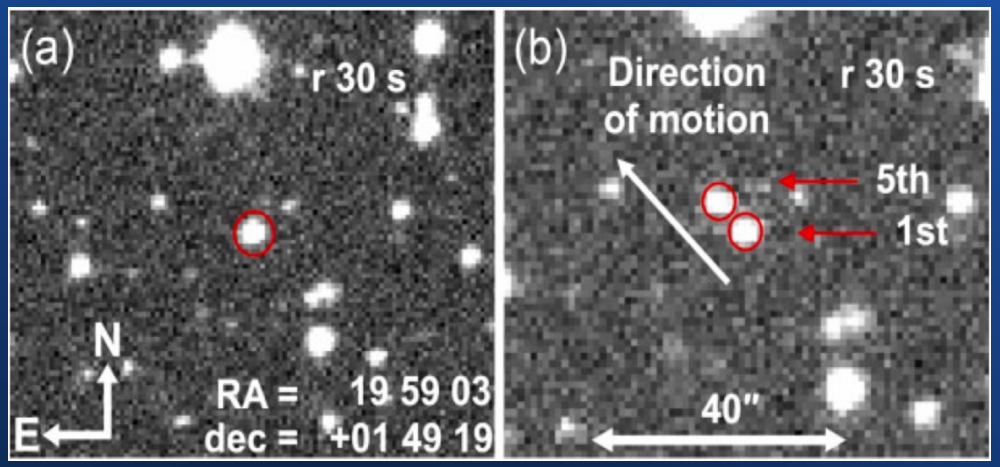
Deep learning enables scalable pattern recognition in complex dynamical datasets

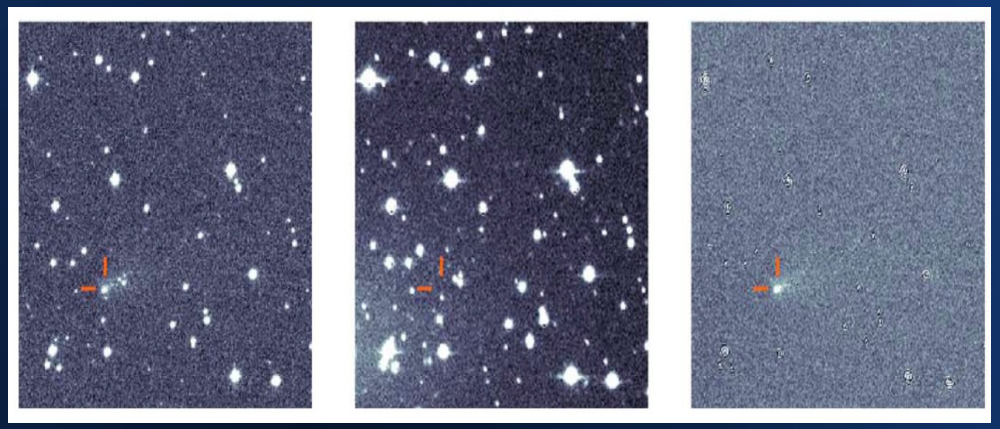
Deep Learning for Moving-Object Detection



- Modern surveys generate millions of transient and moving-object detections.
- Deep-learning pipelines identify cometary activity directly from survey images.

Deep Learning for Moving-Object Detection

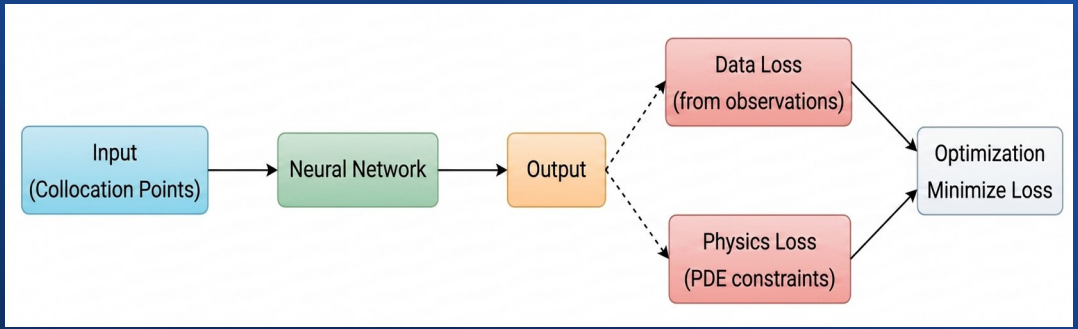




- Modern surveys generate millions of transient and moving-object detections.
- Deep-learning pipelines identify cometary activity directly from survey images.
- Rubin/LSST-scale surveys require automated real-time detection workflows.
- Bolin and Coughlin (2024); Inno et al. (2024)

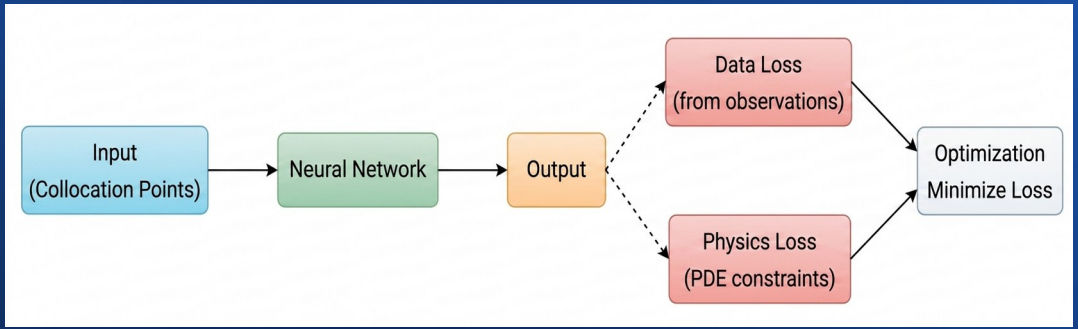
Deep learning enables scalable real-time discovery of moving objects

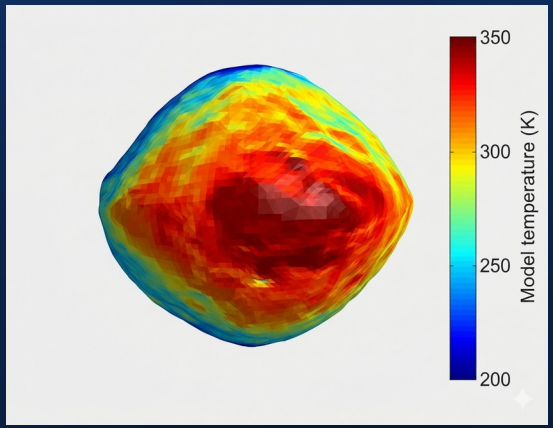
Physics-Informed Neural Networks (PINNs)

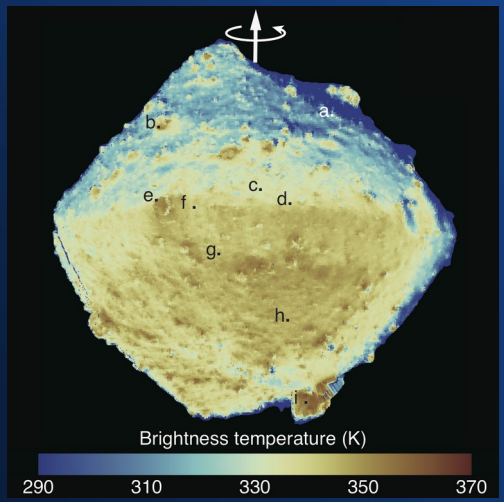


- PINNs embed physical laws directly into neural-network training.
- Physics constraints improve stability and physical consistency.

Physics-Informed Neural Networks (PINNs)



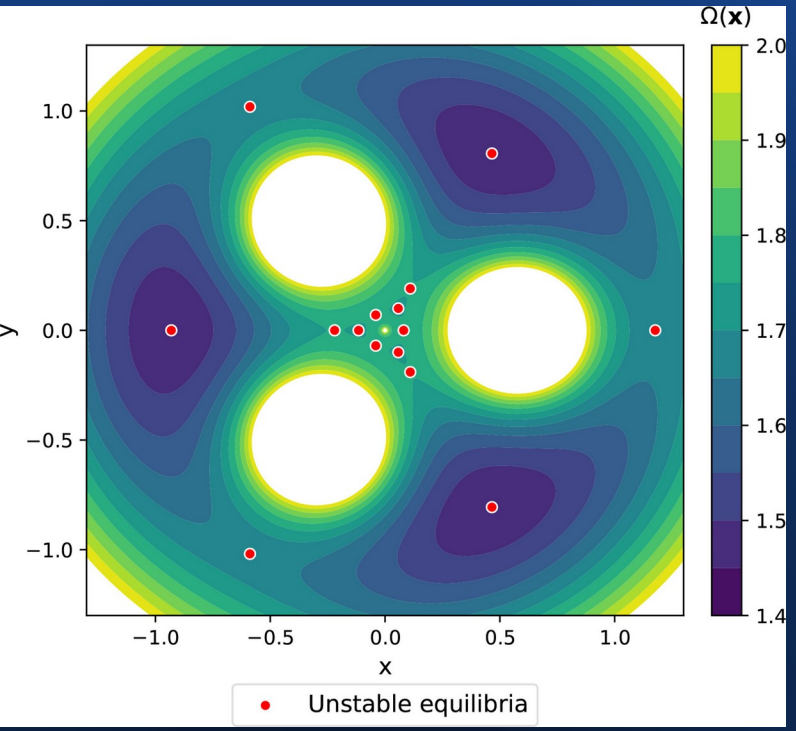


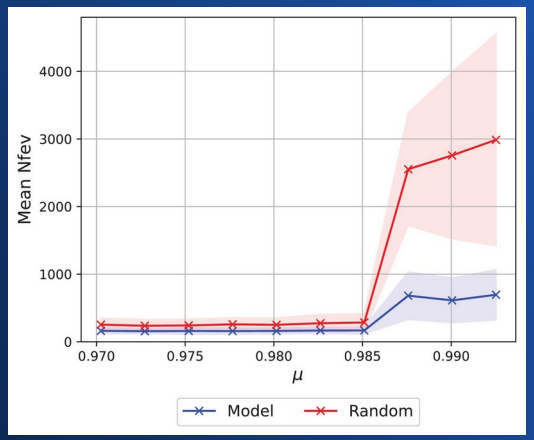


- PINNs embed physical laws directly into neural-network training.
- Physics constraints improve stability and physical consistency.
- PINN and DeepONet approaches can accelerate thermophysical and orbital simulations by orders of magnitude.
- Raissi et al. (2019), Schiassi et al. (2022), Zhao et al. (2024, 2025)

Physics-informed AI combines machine learning with the governing equations of celestial mechanics

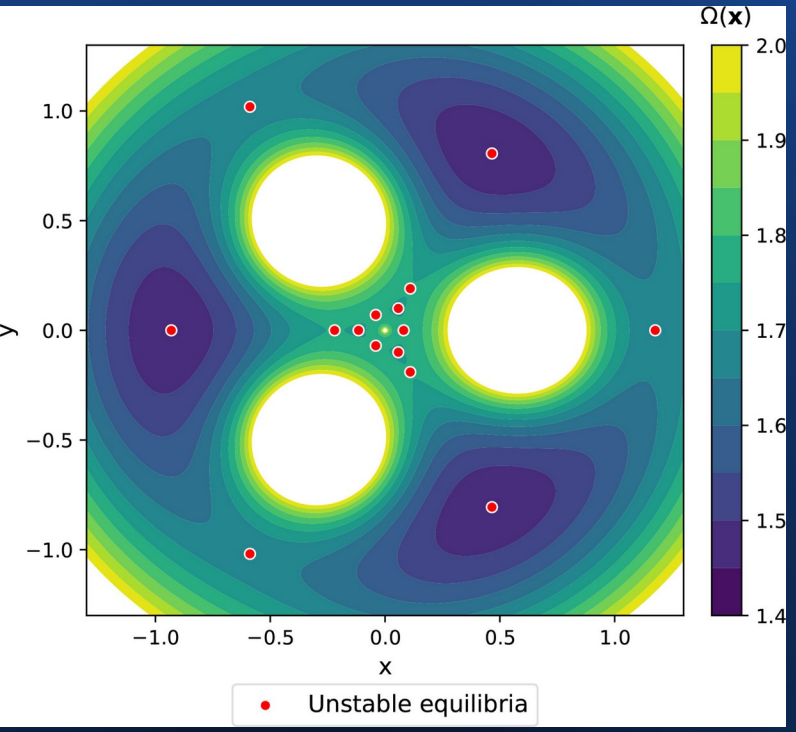
Generative ML for Dynamical Equilibria

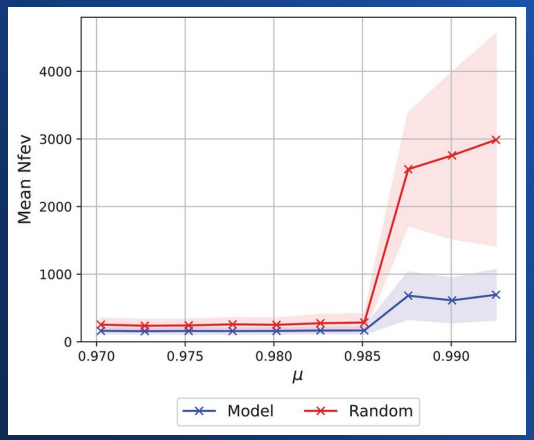




- Flow-based generative models learn the equilibrium-point distribution.
- In the uncertain five-body problem, they recover equilibria for previously unseen mass parameters.

Generative ML for Dynamical Equilibria



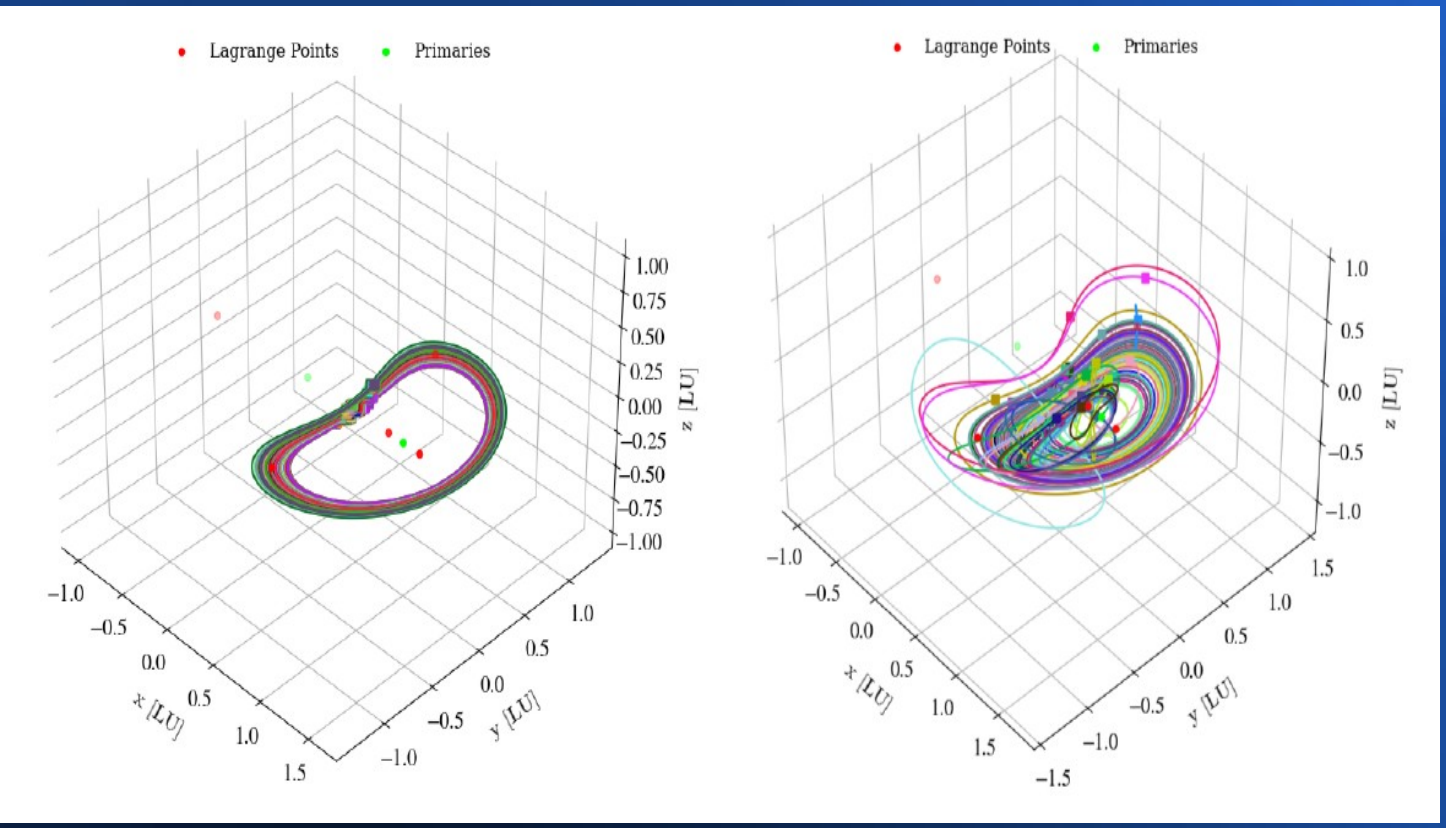


- Flow-based generative models learn the equilibrium-point distribution.
- In the uncertain five-body problem, they recover equilibria for previously unseen mass parameters.
- Generative sampling can substantially reduce the search cost relative to uniform random sampling.

- Wilson and Vasile (2026)

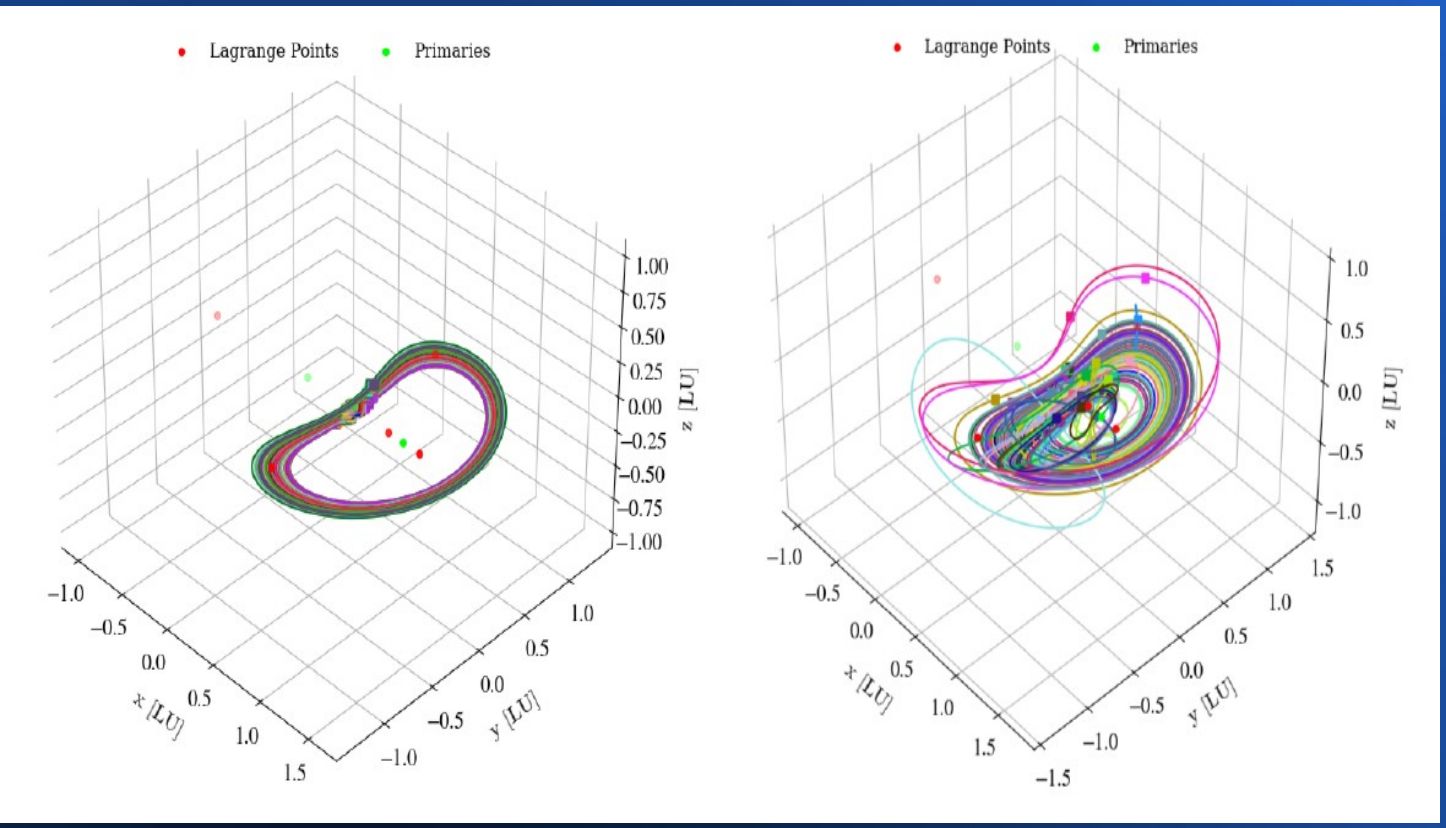
Generative ML can guide the search for dynamical equilibria under uncertainty

Generative AI for Periodic Orbits



- A variational autoencoder learns a latent representation of CR3BP periodic-orbit families.
- Structured exploration of the latent space generates candidate trajectories and moves between orbital families.

Generative AI for Periodic Orbits



- A variational autoencoder learns a latent representation of CR3BP periodic-orbit families.
- Structured exploration of the latent space generates candidate trajectories and moves between orbital families.
- Classical differential correction then refines generated candidates into physical periodic solutions.
- Litteri et al. (2025)

AI proposes new trajectories; celestial mechanics turns them into physical solutions

From Machine Learning to AI Assistants

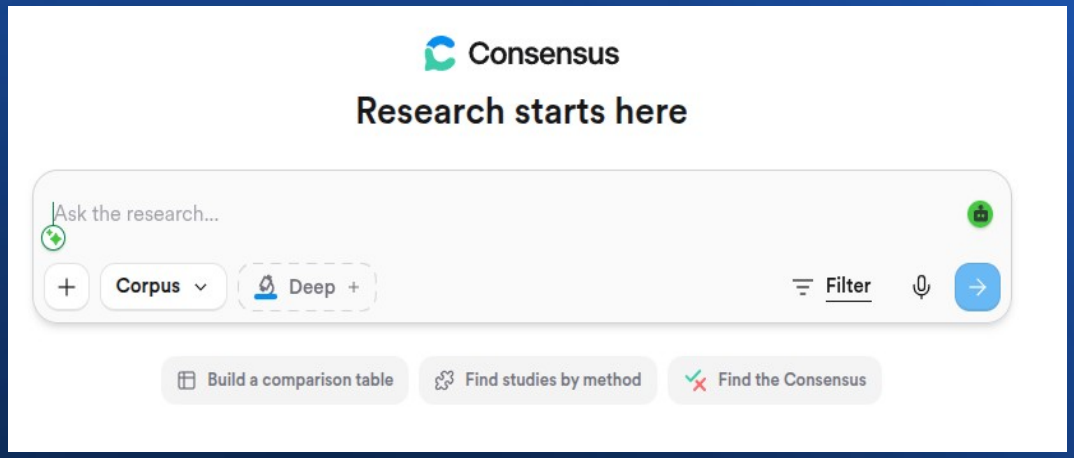
The Next Revolution

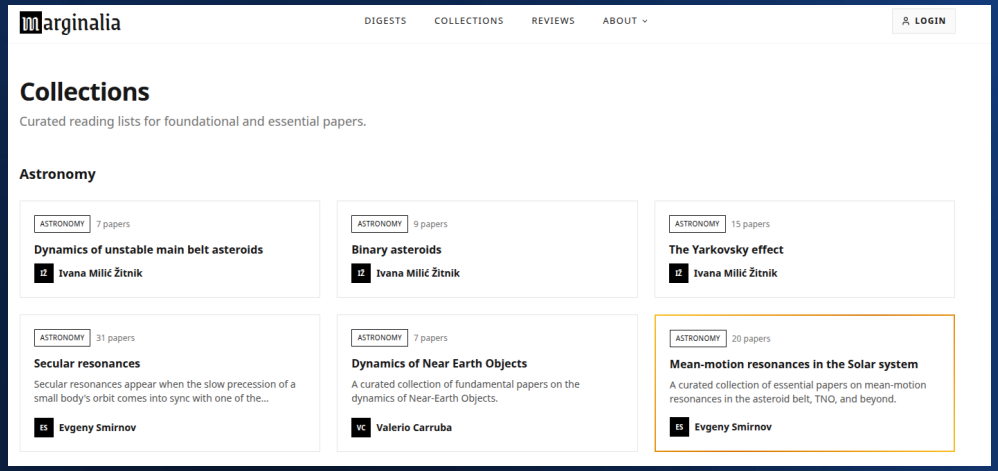
- Traditional ML
- Deep Learning
- Foundation Models
- Large Language Models
- AI Agents
- Autonomous AI



AI is evolving from recognizing patterns to helping conduct scientific research.

LLMs for Scientific Literature Review

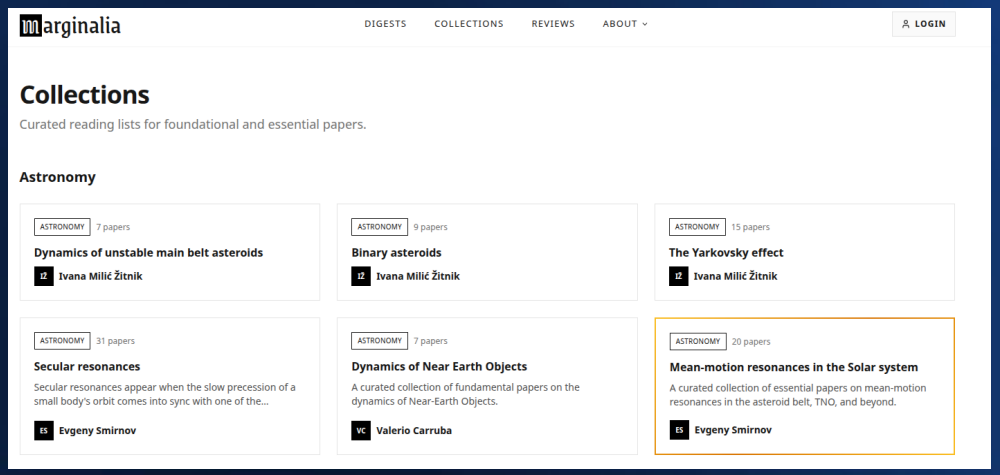




- LLM-assisted tools accelerate scientific literature exploration and synthesis.

LLMs for Scientific Literature Review

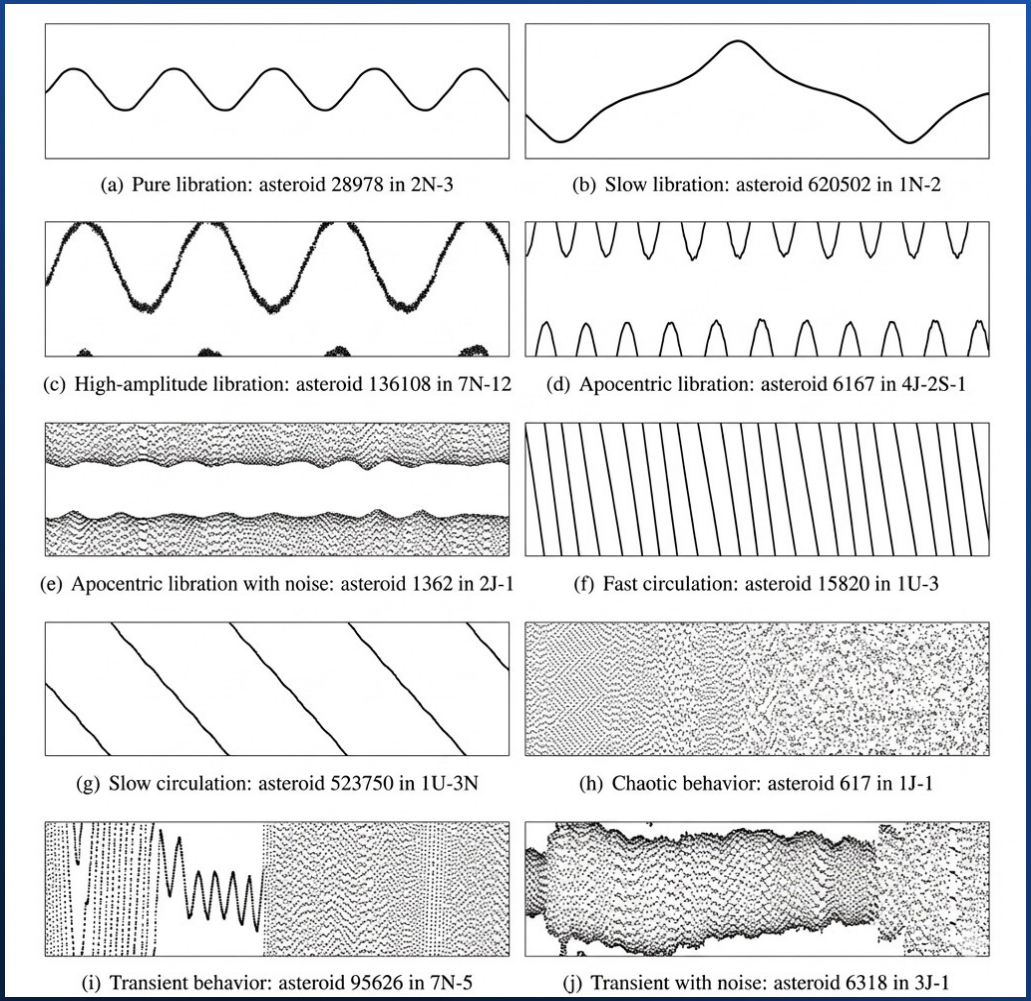
Scan for the cited-paper collection



- LLM-assisted tools accelerate scientific literature exploration and synthesis.
- Retrieval-based systems help researchers identify relevant papers and connect concepts across disciplines.
- LLMs are increasingly used as scientific copilots in astronomy workflows.
- Consensus.app, Marginalia

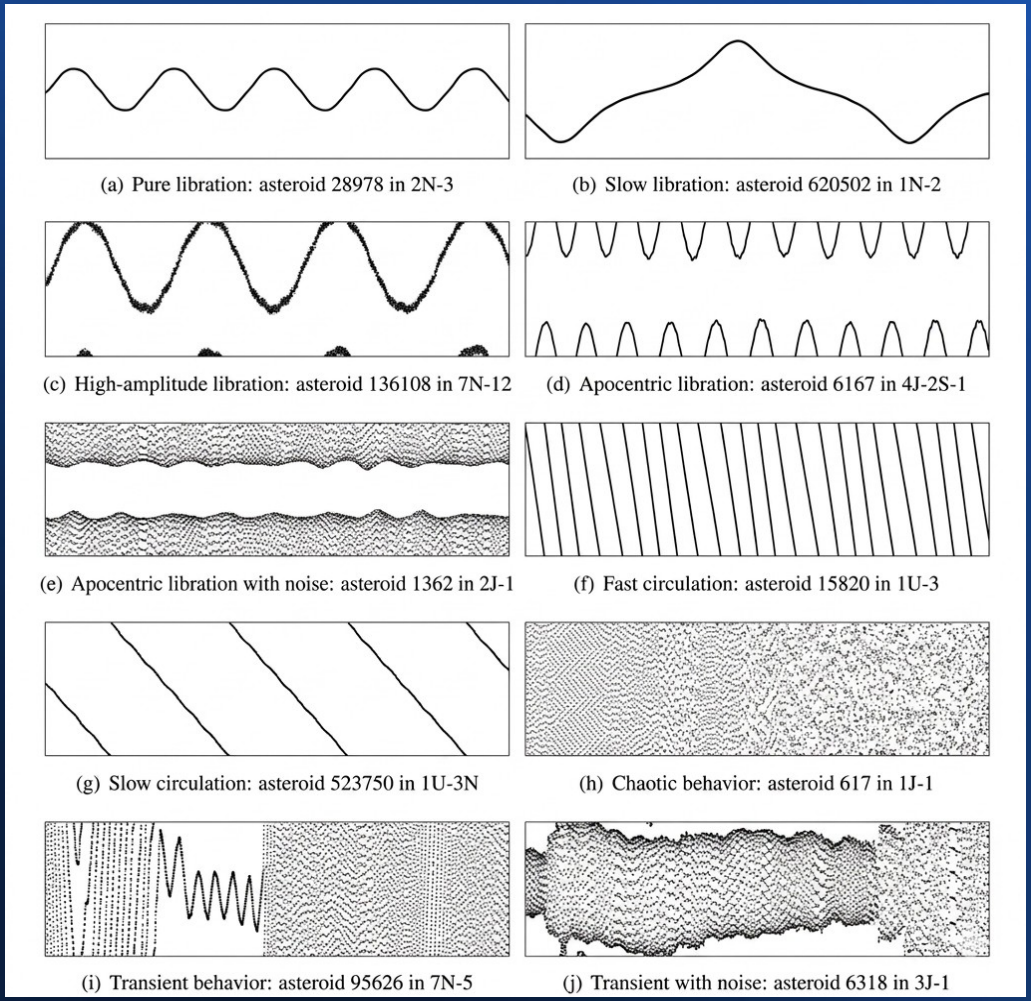
In the Rubin era, literature synthesis and scientific interpretation will become increasingly AI-assisted

Multimodal LLMs for Resonance Classification



- Modern multimodal LLMs can classify resonant behavior directly from images.
- Commercial and open-source models showed strong classification performance without task-specific training.

Multimodal LLMs for Resonance Classification

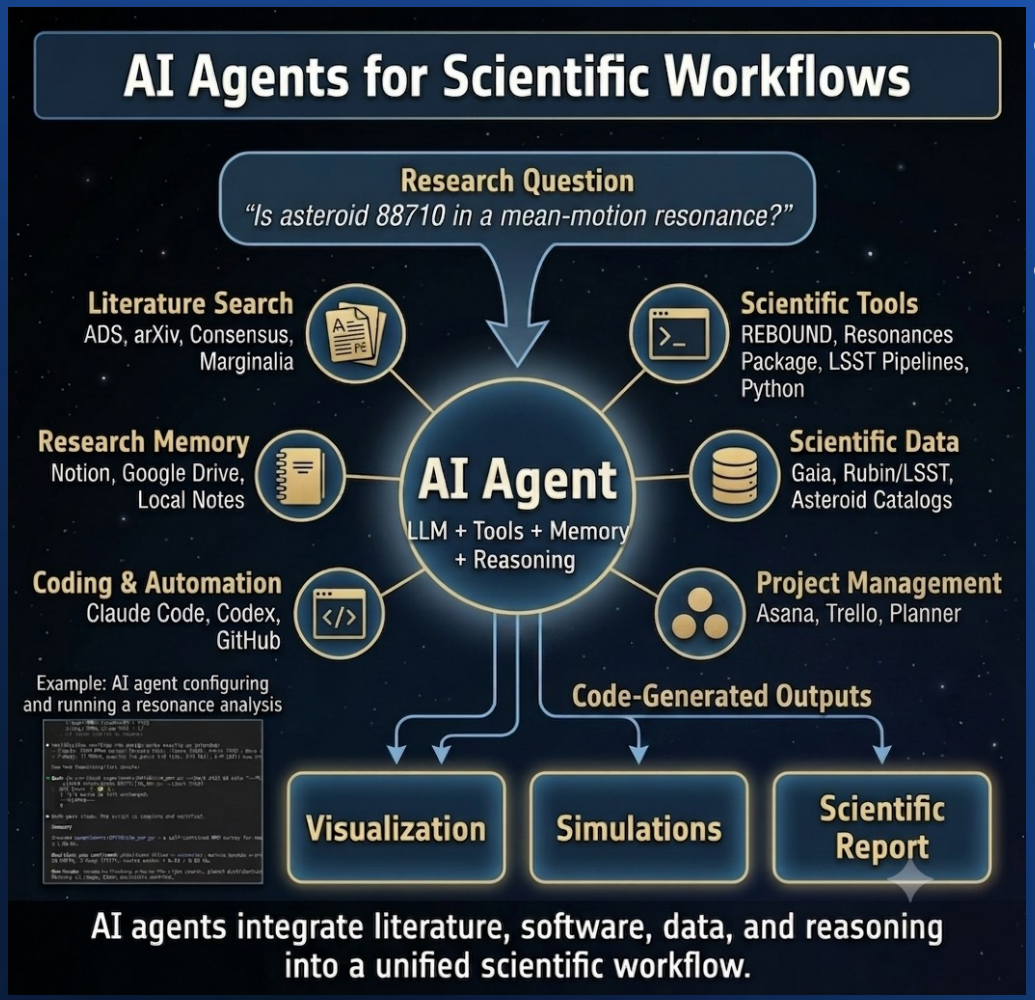


- Modern multimodal LLMs can classify resonant behavior directly from images.
- Commercial and open-source models showed strong classification performance without task-specific training.
- Multimodal LLMs may become scalable assistants for dynamical classification.

- Smirnov (2024), Smirnov and Carruba (2026)
- GPT, Claude, Gemini, Llama, Gemma

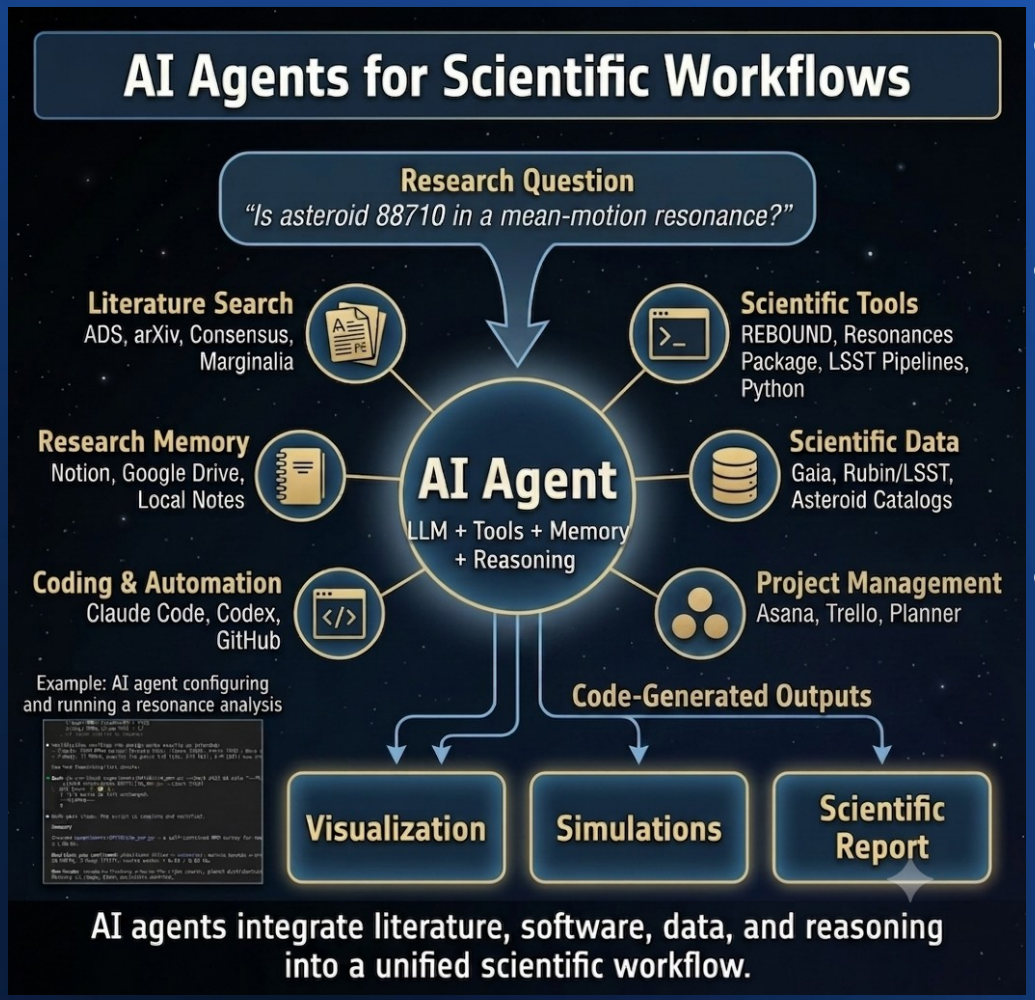
Multimodal LLMs can recognize complex dynamical patterns without explicit feature engineering

AI Agents for Scientific Workflows



- LLMs become agents when connected to tools and data.
- Agents can search literature, write code, run simulations, and analyze results.

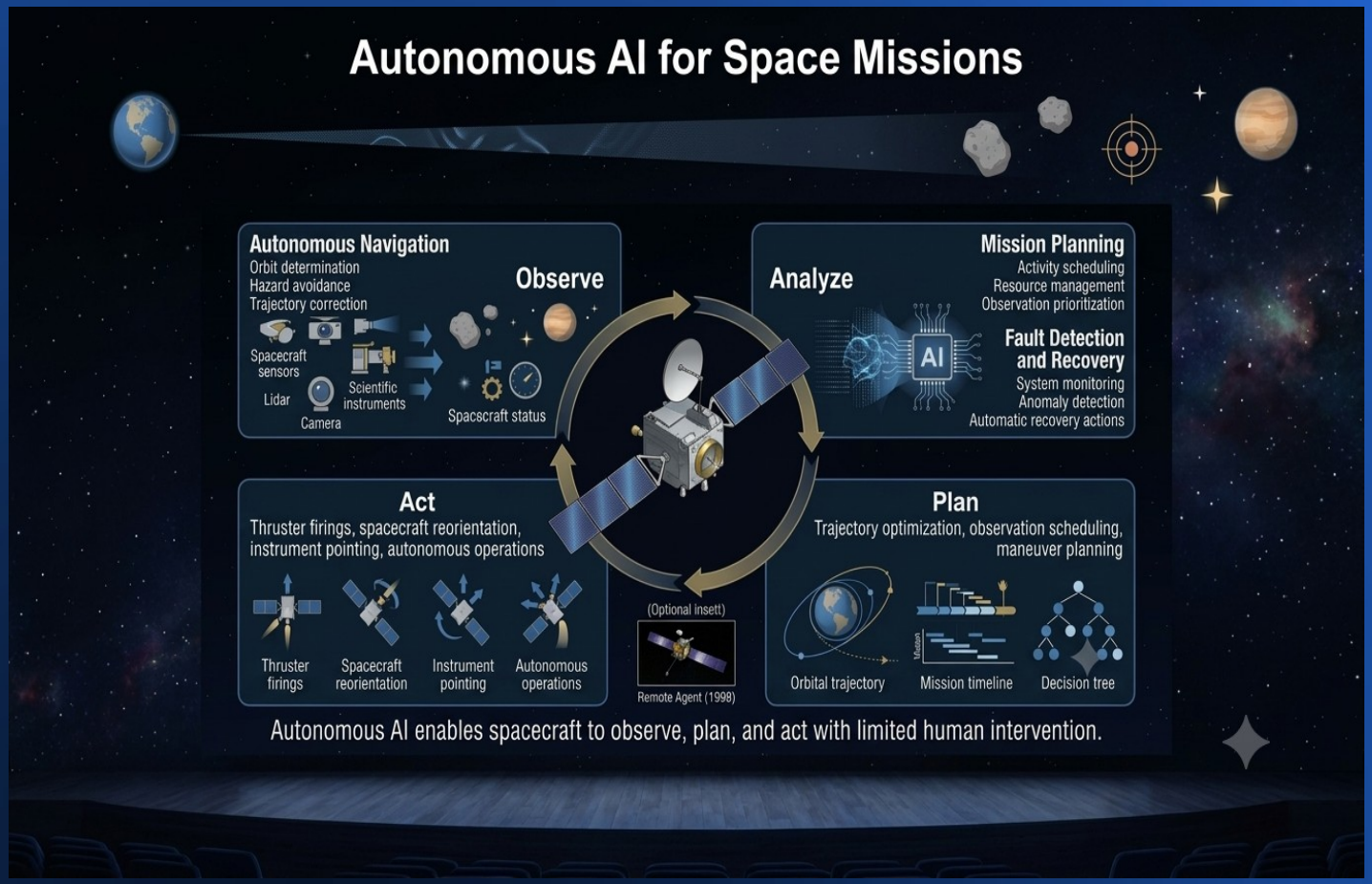
AI Agents for Scientific Workflows



- LLMs become agents when connected to tools and data.
- Agents can search literature, write code, run simulations, and analyze results.
- Scientific workflows increasingly combine AI reasoning with software automation.
- Examples: Claude Code, Codex, MCP-enabled assistants.

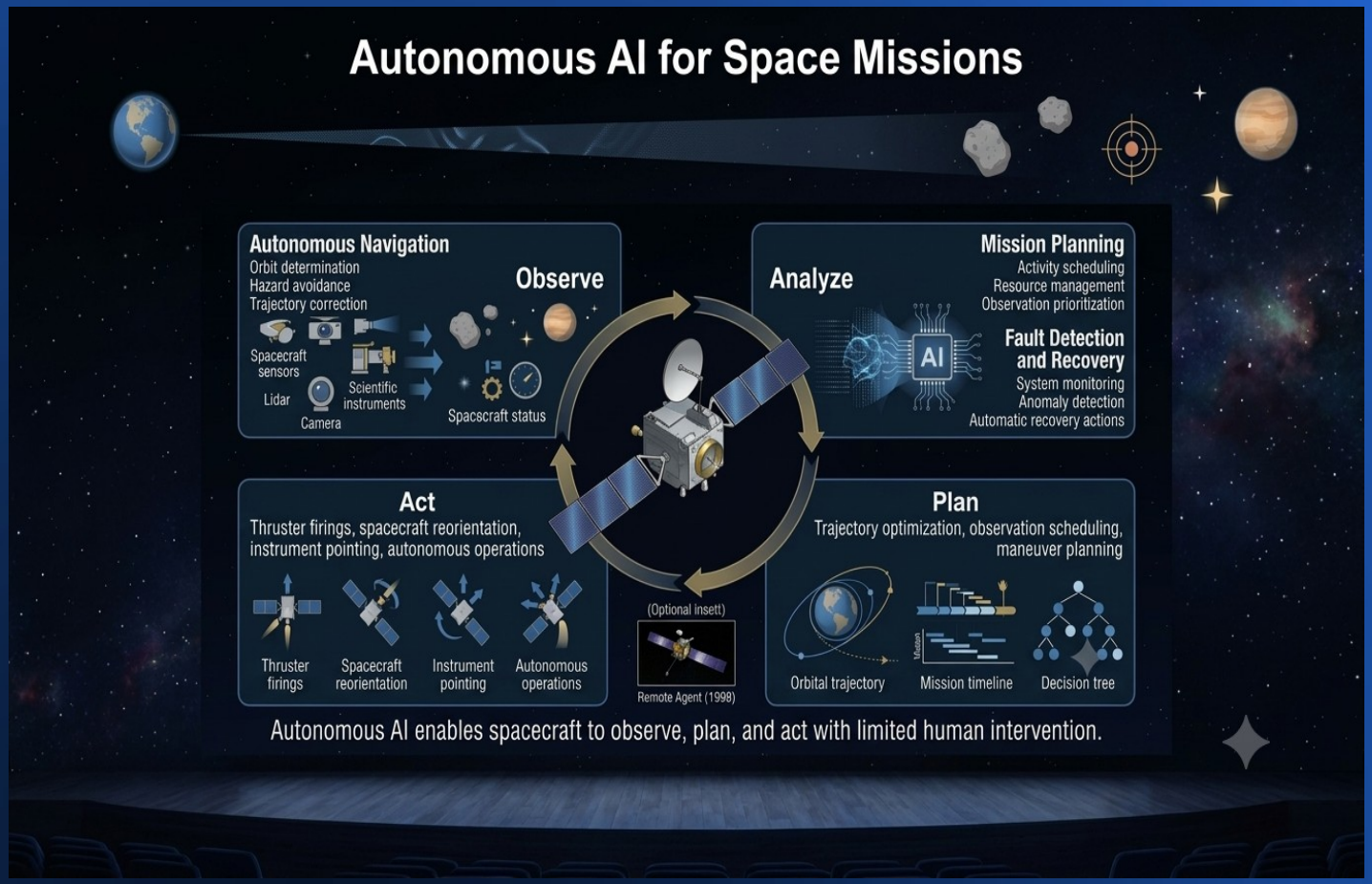
AI agents connect reasoning, software, and scientific data into a single research workflow

Autonomous AI for Space Missions



- Deep Space 1 demonstrated autonomous planning and fault recovery.
- Reinforcement learning: guidance and maneuver optimization.

Autonomous AI for Space Missions



- Deep Space 1 demonstrated autonomous planning and fault recovery.
- Reinforcement learning: guidance and maneuver optimization.
- Autonomous operations: navigation and spacecraft inspection.
- Future missions will increasingly require onboard decision-making beyond Earth orbit.

- Muscettola et al. (1998), Gaudet et al. (2020)

Autonomous AI reduces dependence on ground control and enables faster onboard decisions

AI in the Rubin Era



Rubin LSST Data Stream

Millions of Solar-System detections and alerts

AI-Assisted Scientific Pipeline

Detection

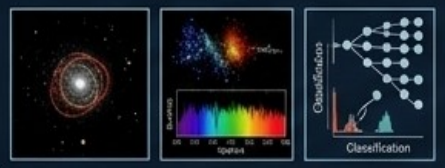
CCD

Active asteroids
Comets
Unusual activity



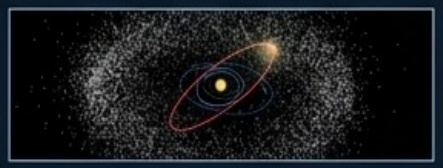
Classification

Asteroid taxonomy
Asteroid families
Resonant populations



Discovery

Rare objects
Anomaly detection
New dynamical structures



Follow-up

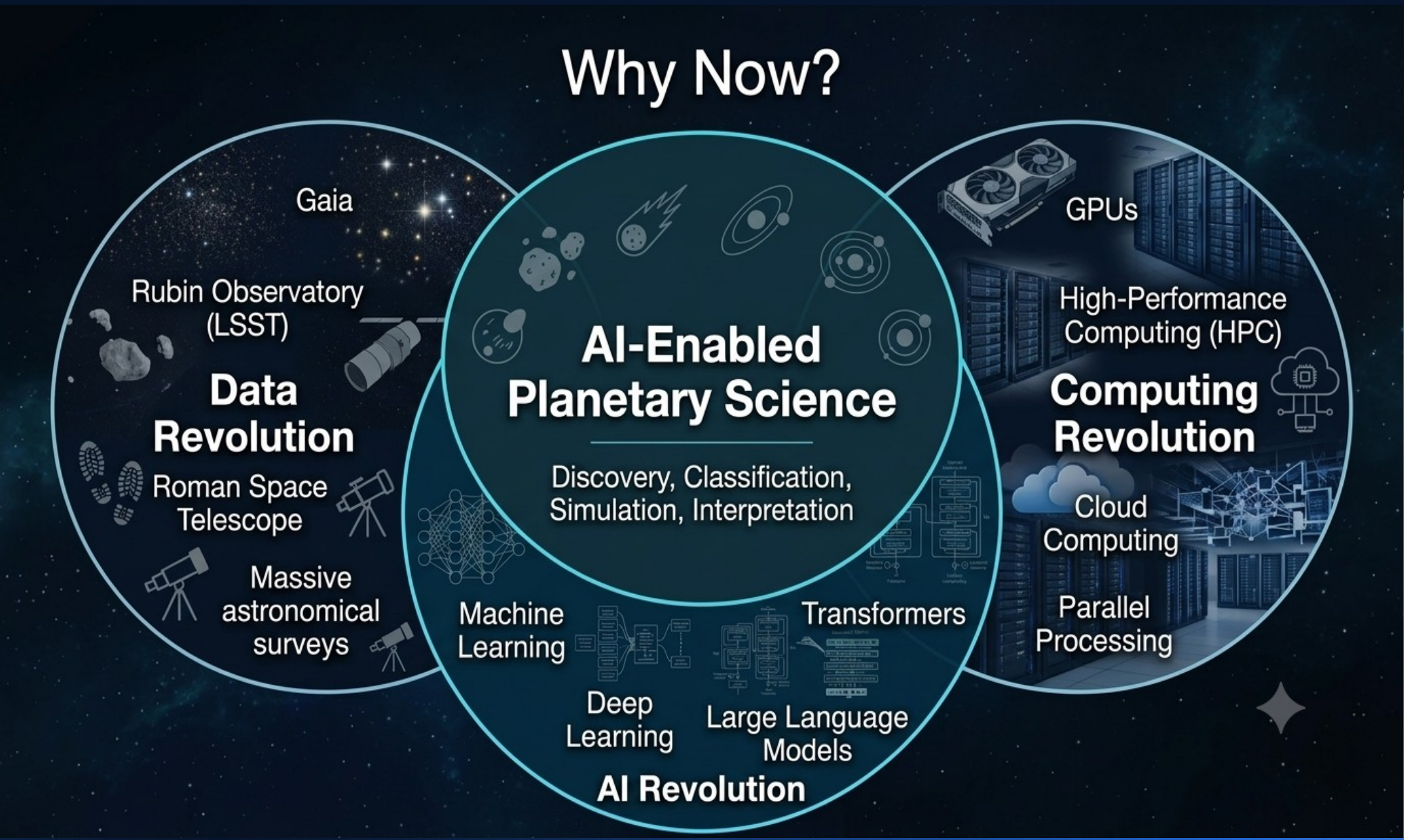
Alert filtering
Observation prioritization
Resource allocation



Scientific Discovery

New populations
Solar-System evolution
Physical characterization
Dynamical processes

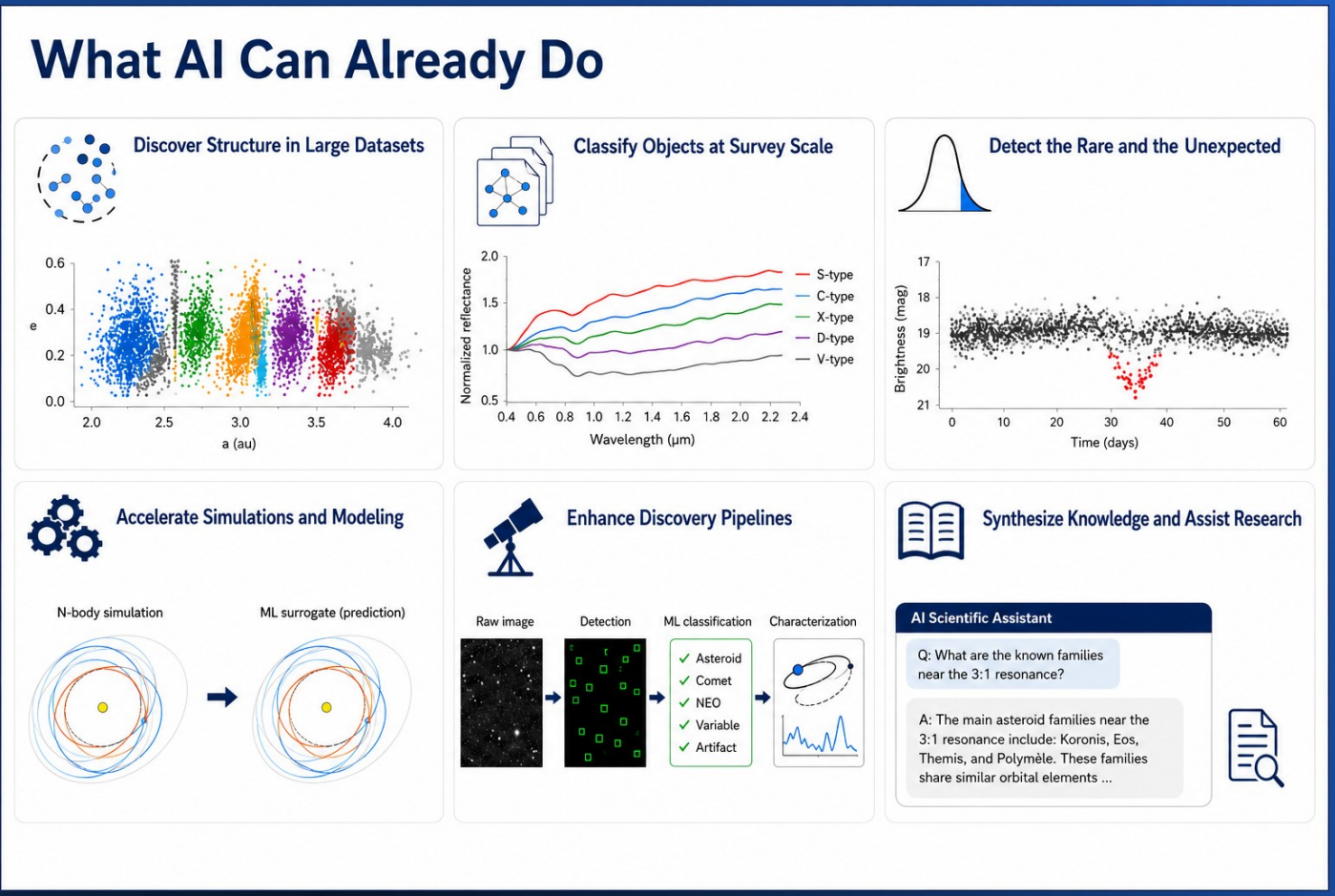
Many discoveries remain hidden in petabyte-scale datasets until AI highlights unusual objects and unexpected behavior



Three revolutions are happening simultaneously

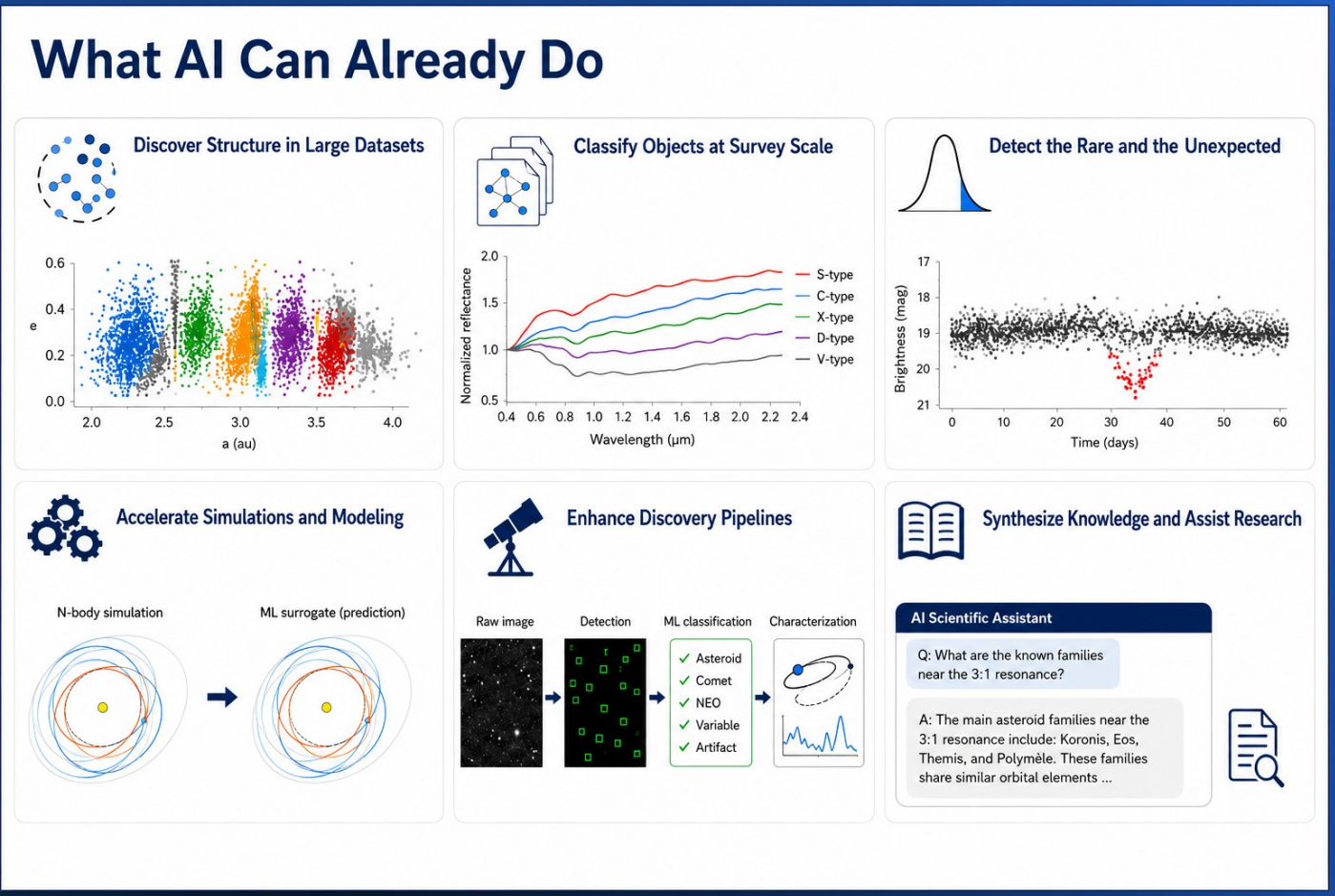
Planetary science sits at the intersection of these three

What AI Can Already Do



- Detect hidden patterns in large multidimensional datasets.
- Automate classification and candidate discovery at Rubin/LSST scale.

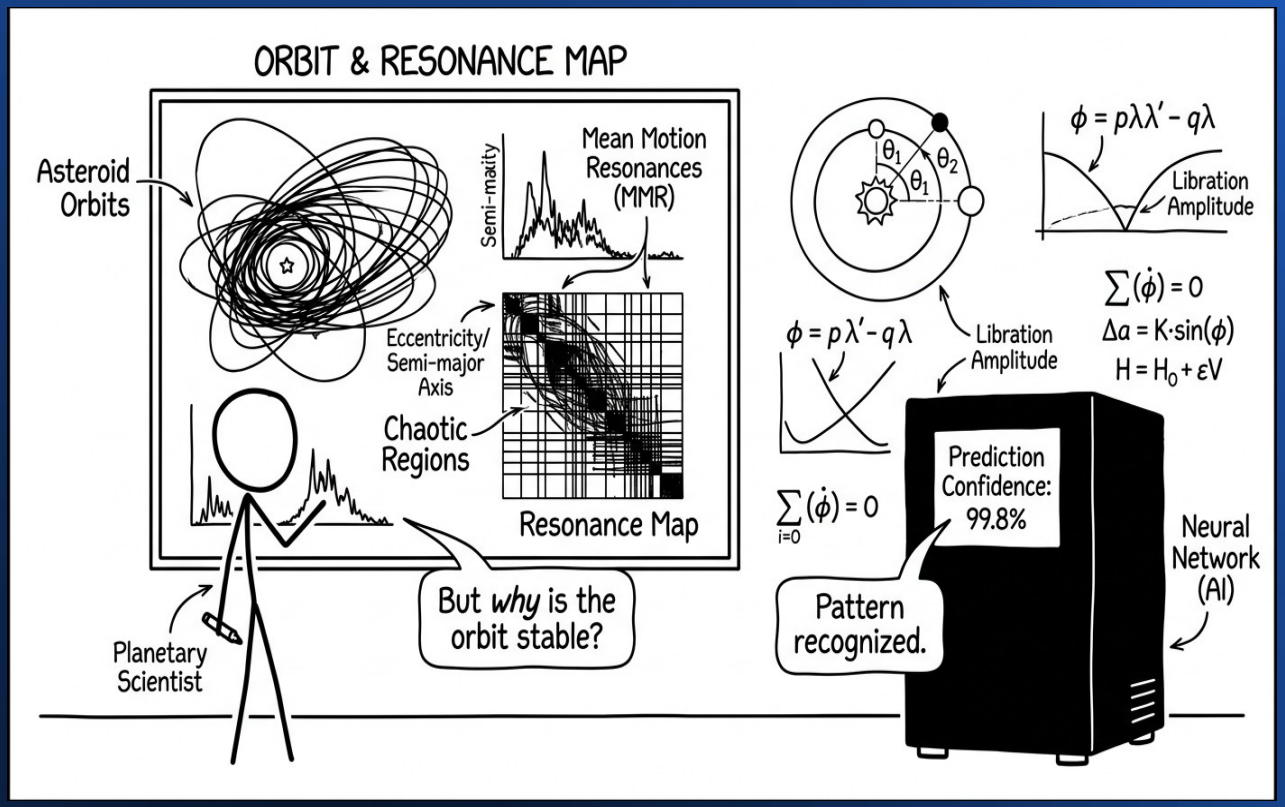
What AI Can Already Do



- Detect hidden patterns in large multidimensional datasets.
- Automate classification and candidate discovery at Rubin/LSST scale.
- Accelerate simulations, software development, and scientific workflows.

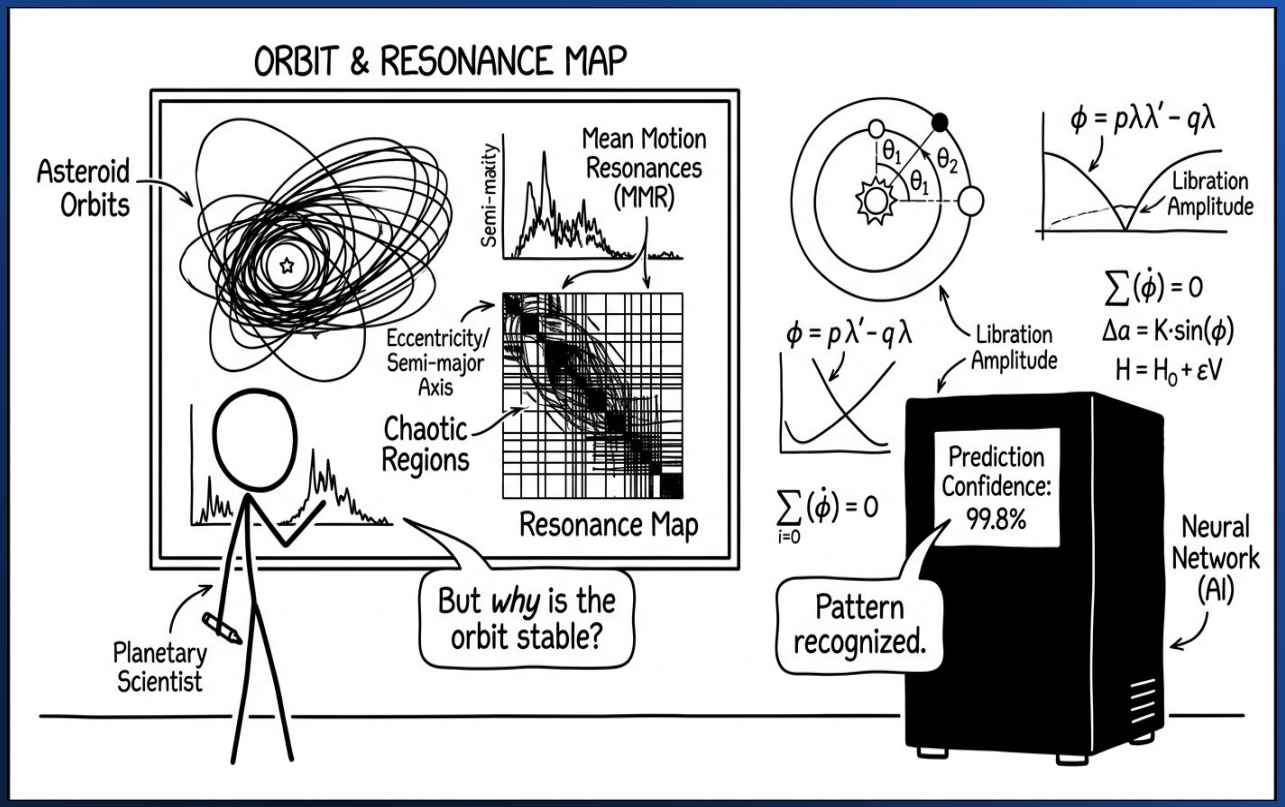
AI is becoming a scalable research assistant for the data-intensive era of astronomy

What AI Cannot (Yet) Do



- ML cannot replace physical understanding or causal reasoning.
- Performance outside well-characterized domains should be evaluated carefully.

What AI Cannot (Yet) Do



- ML cannot replace physical understanding or causal reasoning.
- Performance outside well-characterized domains should be evaluated carefully.
- Scientific validation remains essential, regardless of whether hypotheses originate from humans or AI.

Physics, interpretation, and scientific judgment remain

Final Vision



- Rubin-era astronomy will require scalable intelligent analysis.

Final Vision



- Rubin-era astronomy will require scalable intelligent analysis.
- The future of celestial mechanics may combine first-principles physics with AI-assisted discovery and scientific workflows.

The bottleneck is shifting from data acquisition to scientific interpretation

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- W. C. Fraser
- A. Penttilä
- B. Bolin
- R. S. Souza
- A. Krone-Martins
- E. Ishida

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- W. Barletta
- M. V. F. Lourenço

New Generation

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- M. M. Bala
- R. D. Z. Pedroso
- E. M. D. S. Delfino

Honorable Mentions

Classical Machine Learning

- Random Forests
- Support Vector Machines (SVM)
- XGBoost / LightGBM
- Gaussian Processes
- Bayesian Networks
- Hidden Markov Models

Unsupervised Learning

- DBSCAN
- Hierarchical Clustering
- Principal Component Analysis (PCA)
- t-SNE / UMAP

Deep Learning

- Autoencoders
- LSTMs / GRUs
- Graph Neural Networks (GNNs)
- Generative Adversarial Networks (GANs)
- YOLO

Physics & Scientific AI

- Symbolic Regression
- Surrogate Modeling
- Reinforcement Learning
- Differentiable Simulations

Foundation Models

- Retrieval-Augmented Generation (RAG)
- Transformers/Multimodal Models
- Scientific Copilots

Not discussed here, but increasingly relevant in scientific AI