

Low-cost Adaptation of a Geometry Foundation Model for Bayesian Shape Inference

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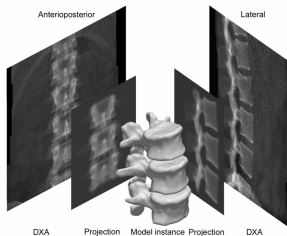
EuCAIFCon 2026, Heidelberg, 28th August 2026



PHYSICS X

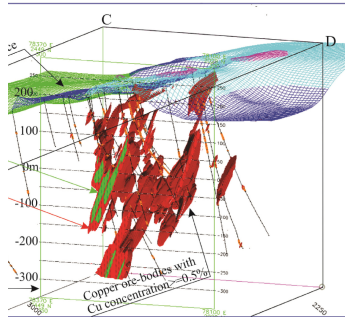
Why do we Want to Infer Shapes?

Medical Imaging and Radiology



Whitmarsh et al. 2013

Geological Subsurface Modelling



Xuan et al. 2024

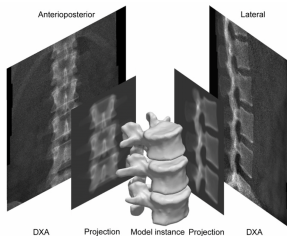
Asteroid Lightcurve Inversion



Image Credits: ESA,
NASA/JHU APL, JAXA

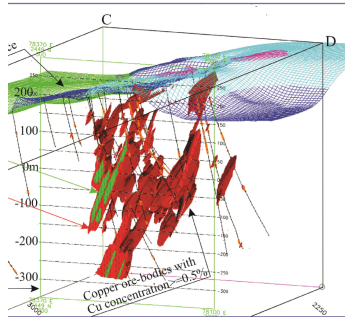
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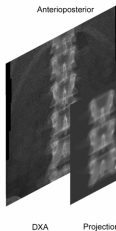
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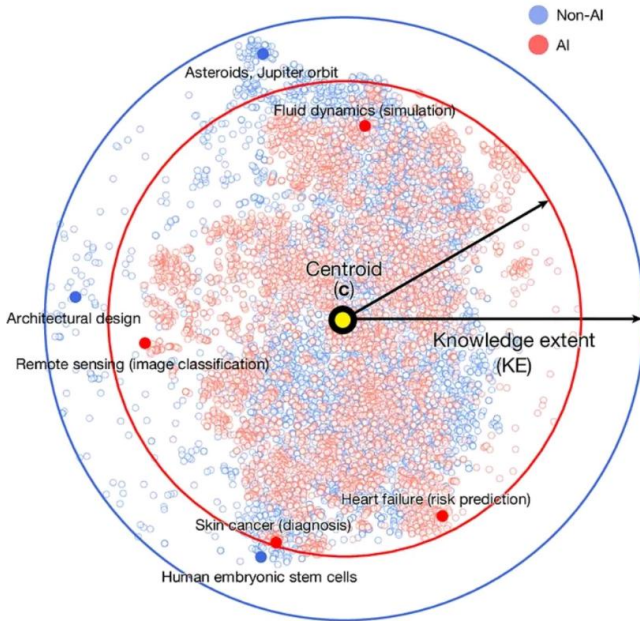
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Why do

Medical
Research



Whitman



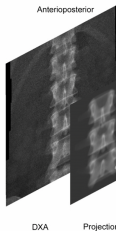
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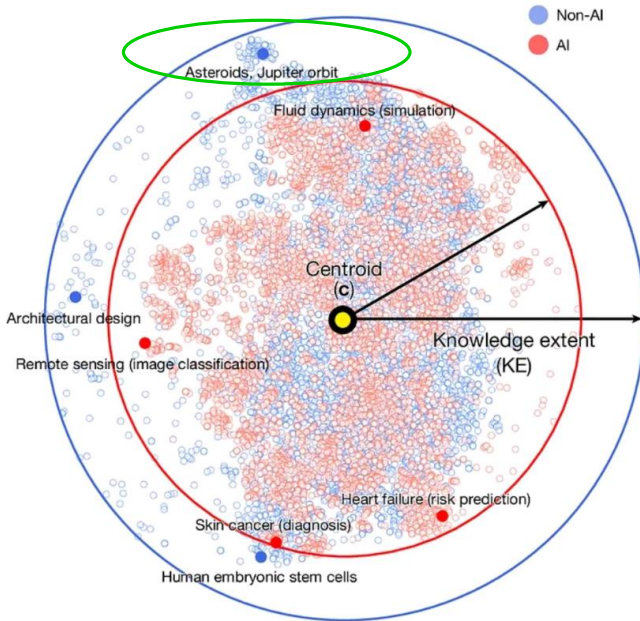
ESA,
JAXA

Why do

Medical
Research



Whitman



Intercurve
on



ESA,
JAXA

Challenges in Shape Inference

Geometries are Potentially Infinitely Complex

So the inverse problem of determining them from sparse noisy measurements is hugely ill-posed.

How to Parameterize a Shape?

CAD parameters are normally not available, mesh vertices are incredibly high dimensional and variable in size.

Incorporating What is Reasonable

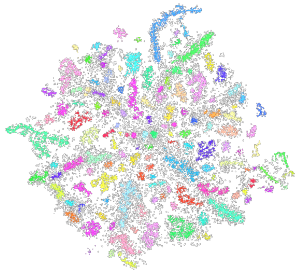
Plenty of domain knowledge of what looks reasonable, typically very hard to quantify.



Building on a Foundation Model

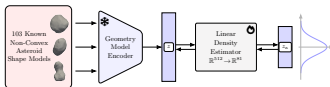
1. Geometry Foundation Model Latent Space

Provides a moderate dimension, well-conditioned and connected space over geometries.



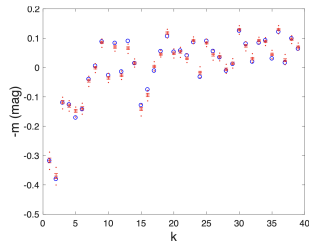
2. Learn a Prior using Example Geometries

Impose domain knowledge on the inverse problem, while avoiding need to state explicitly what is reasonable



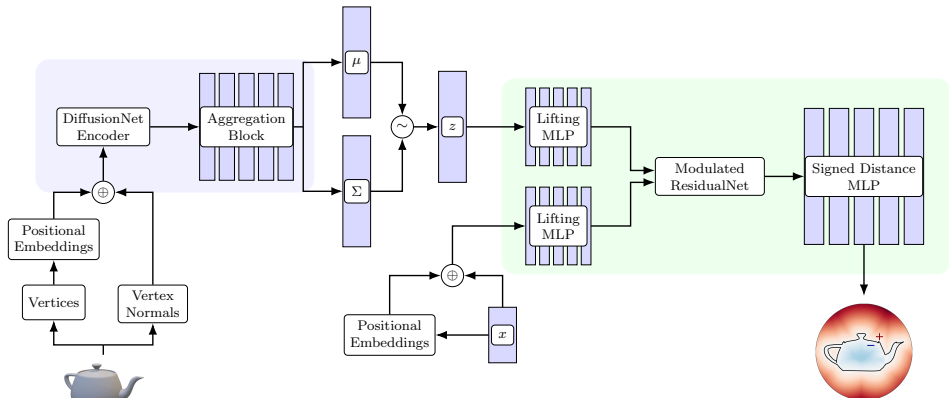
3. Construct a Differentiable Forward

Opens the problem up to the plethora of standard methods for tackling Bayesian inference problems.



Muinonen et al. 2020

The Geometry Foundation Model



Sharp et al. 2022; Mehta et al. 2021; Deitke et al. 2023; Koch et al. 2018; Gropp et al. 2020

What do we Actually want from our Prior?

Low-Dimensional

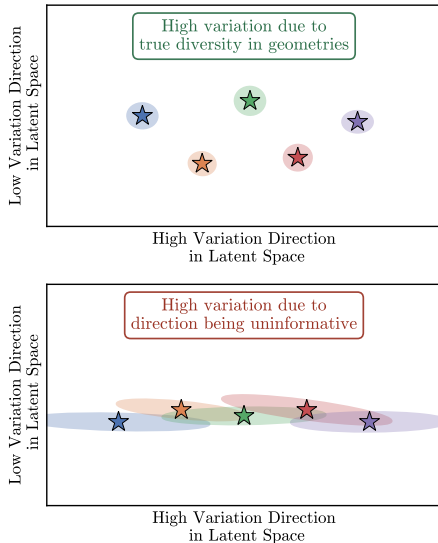
512 dimensions is excessive for asteroids, they are not that complex and we only have a few dozen observations for each.

Low-Data

We are constructing the prior from only 103 example asteroid geometries, we are not data rich.

Lightweight

We aim to build this into a forward / simulator, the sampling or evaluating the PDF should be subdominant to the rest of the forward.



A Lightweight Prior over Latents

A linear model for the latents, in analogy to PPCA:

$$z = A z_a + b + \epsilon \quad \Rightarrow \quad \pi(z) = \mathcal{N}(b, AA^\top + \sigma^2 I)$$

Maximize Geometries not Latents

Fit A, b, σ to maximise the likelihood of the decoded geometries $\{M_i\}$, not the latent codes $\{z_i\}$:

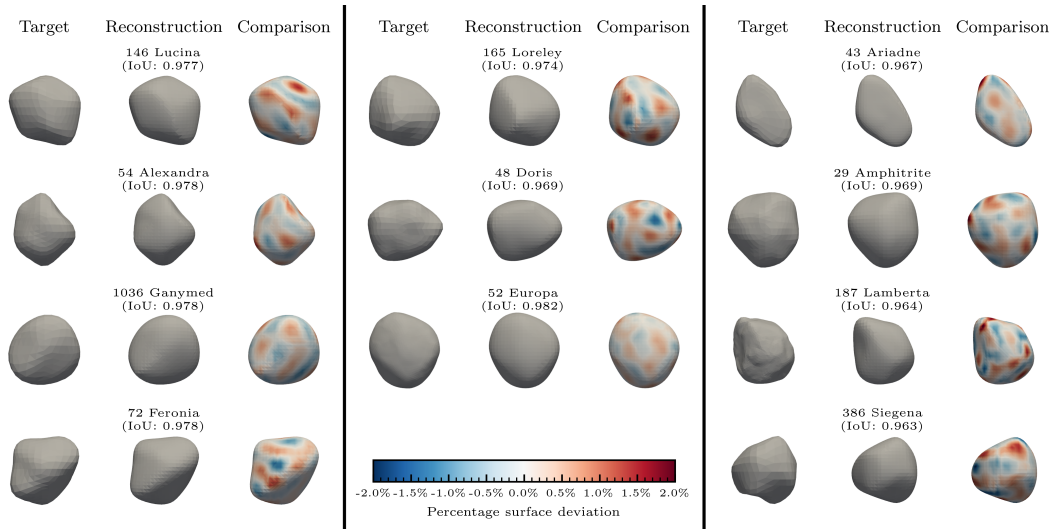
$$p(\{M_i\}_{i=1}^N | A, b, \sigma) = \prod_{i=1}^N p(M_i | A, b, \sigma)$$

Bayesian view of VAE

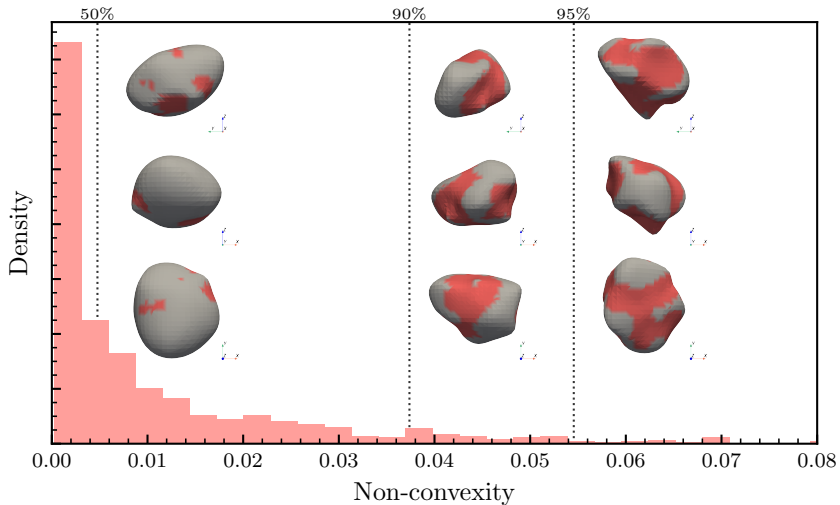
A VAE encoder $q(z_i | M_i) = \mathcal{N}(\mu_z^i, \Sigma_z^i)$, is a variational posterior over latents.

$$p(\{M_i\}_{i=1}^N | A, b, \sigma) = \prod_{i=1}^N \frac{p(M_i) \pi(z_i | A, b, \sigma)}{q(z_i | M_i)}$$

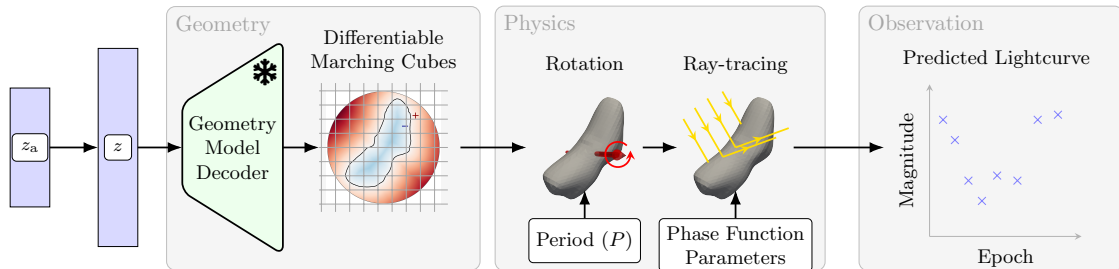
An Expressive Prior over Asteroids



A Reasonable Prior over Asteroids

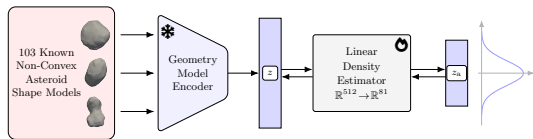


An (Approximately) Differentiable Forward Model

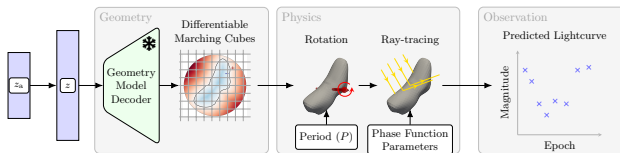


Assembling the Pieces and Bayesian Inference

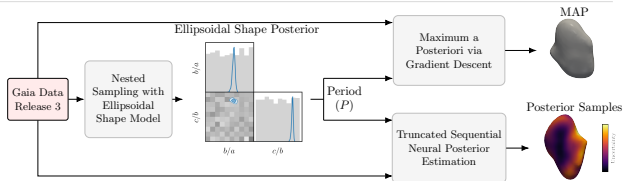
Geometry Priors



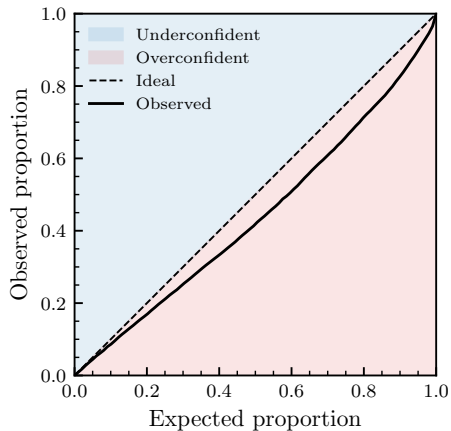
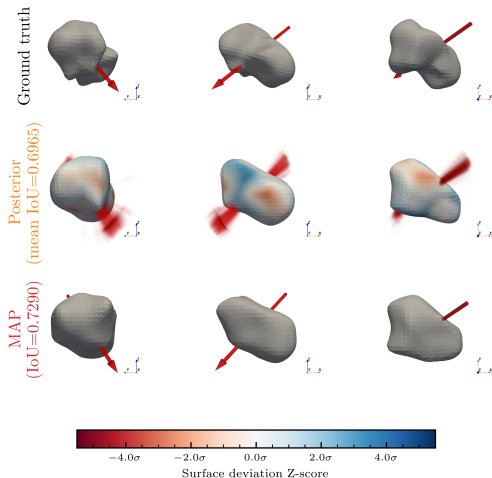
Differentiable Forward



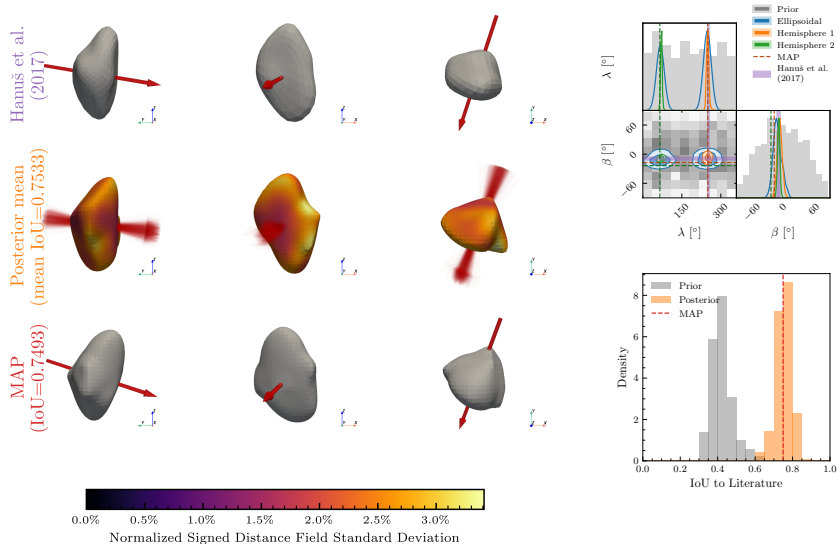
Bayesian Inversion



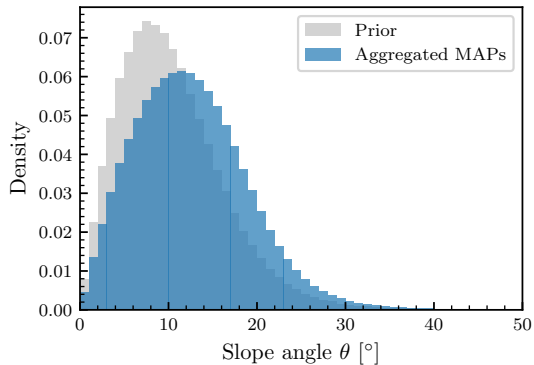
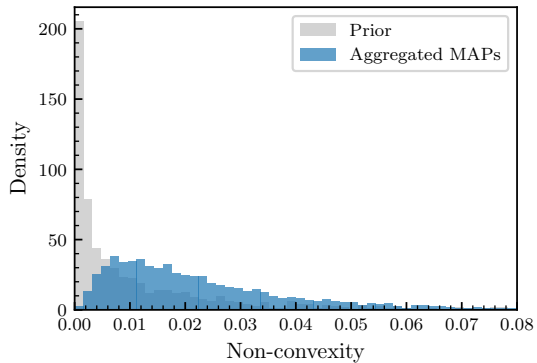
Synthetic Data (Signal Injection)



Example: Case Study 43 Ariadne



Population Statistics



Limitations and Future Work

Limitations

- ▶ The **prior** is built from existing literature shape models, **biased** toward larger, brighter, and near-Earth objects where resolved imaging is feasible.
- ▶ Assumes **constant principal-axis** rotation, so cannot fit tumblers or asteroids with strong YORP evolution; the period is also held fixed during non-convex inference.
- ▶ Finite latent dimensionality caps the scale of recoverable surface detail.

Future work

- ▶ Fully **amortised** simulation based inference, for sub-second Bayesian asteroid shape inference at population scale.
- ▶ **Gaia DR4/DR5** (DR4 alone expected to report $2.6\times$ more asteroid observations) and **LSST** photometry.
- ▶ **Joint inference**, with other observables (e.g. occultation timings, Doppler radar, or dense photometry).

Cranmer et al. 2020; Brown 2025; Ivezić et al. 2019



Conclusions and Takeaways

Foundation Models Facilitate Bayesian Shape Inference

Autoencoding foundation models can provide a well-conditioned regular geometry representation suitable for Bayesian inference.

Learn Priors to Incorporate Domain Knowledge

Constructing a prior from the latent embeddings of $O(100)$ examples is feasible but requires careful consideration of the meaning of the embeddings to ensure you fit what matters.

Machine Learning only what is Needed provides Flexibility

By using machine learning for only the geometric part of the forward, gives flexibility and allows for training free experimentation in other parts of the physics.





PHYSICS X