Master Lab, Master Seminar and BACHELOR PROJEKTGRUPPE

OFFERED BY THE

LEARNING AND OPTIMISATION FOR VISUAL COMPUTING (LOVC) GROUP

&

GEOMETRY IN MACHINE LEARNING (GML) GROUP

INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

Schedule

1. General rules for Bachelor Projektgruppe/Master Lab/Master Seminar
2. 5 Topics for Bachelor Projektgruppe/Master Lab/Master Seminar
   offered by Geometry in Machine Learning Group(GML)
3. 9 Topics for Bachelor Projektgruppe/Master Lab/Master Seminar
   offered by Learning and Optimisation for Visual Computing Group(LOVC)

Rules for Master Lab, Master Seminar and BACHELOR PROJEKTGRUPPE

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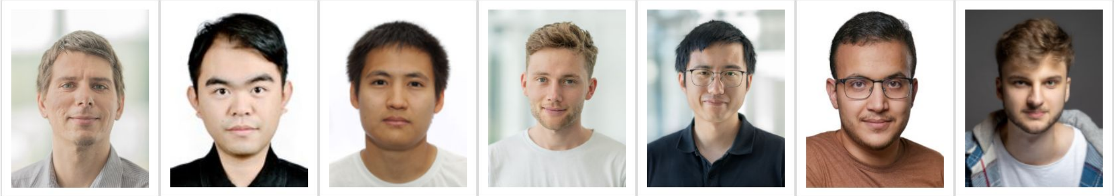
INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

Groups

LOVC Group (Prof. Dr. Florian Bernard):



Prof. Dr. Florian Bernard **Head of Group**	Weikang Wang **PhD Student**	Zhakshylyk Nurlanov **PhD Student**	Paul Roetzer **PhD Student**	Dongliang Cao **PhD Student**	Nafie El Amrani **PhD Student**	Tobias Weissberg **PhD Student**

Geometry in ML Group (JProf. Dr. Zorah Lähner):

Zorah Lähner Head of Group	Hongyu Zhou PhD student	Lio Schmitz PhD student	Mohamed Ebbed PhD student	Ipsit Mantri PhD student

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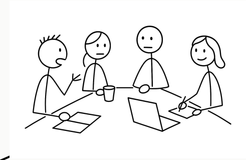
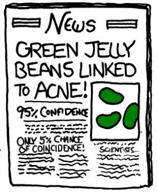
Timeline





Today	21.10.2025	24.10.2025	tba	tba	1 week after presentation
	Choose topics	Topics assigned	Working on Project Meeting with Supervisors	Presentations	Report due

Overview

Workload:

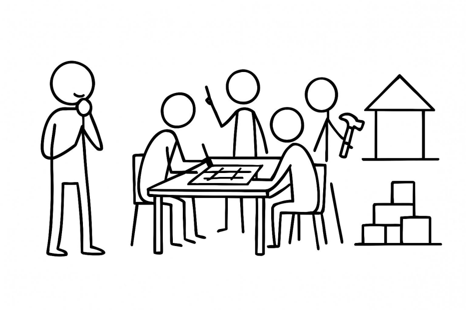
- Literature reading (Seminar, MLab, BPG)
- Implementation (MLab, BPG)

Grading:

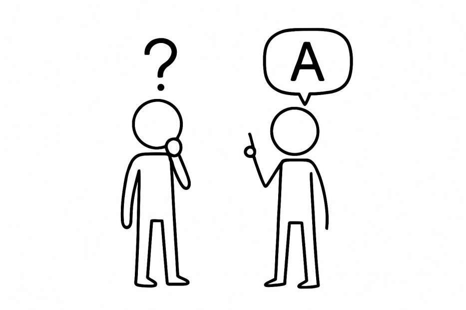
- Presentation
- Report

Supervision

Milestones setting



Meeting (every 1 or 2 weeks)



Answering questions

Presentation practice

Presentation

- Present your work at the end of the semester:
  - 20mins talk + 10mins Q&A/person
- Slides for the talk:
  - Discuss the structure with your supervisor before you start.
  - Trial talk is always a nice option to see if the talk matches the expectations
- Basic requirements:
  - Slide numbers
  - References for figures or text that you directly took from somewhere

Report

- Hand in until 1 weeks after the presentation!
- Written in LaTeX:

  Template available at https://cg.cs.uni-bonn.de/courses.

  Around 10 pages in length.(excluding the reference)
- Sound and comprehensible summary of provided literature and the experiments in your own words.
- Adhere to scientific standards:

  Provide proof for your statements(if any).

  Use references to make your sources transparent.
- State the work division if working in group

Embargo restrictions

1. For those affected by embargo restrictions, pls also apply to the examination office
2. Application should be done together with registration

Topic selection

- Interested in a topic?

  Contact Nafie El Amrani(n.elamrani@uni-bonn.de) (>= 3 topics)

- Slides for organization and topics are available on our homepage:

  https://lovc.cs.uni-bonn.de/index.php/teaching/

  https://geometryinml.cs.uni-bonn.de/teaching/

  (⚠️ slides only accessable while in Uni Bonn network)

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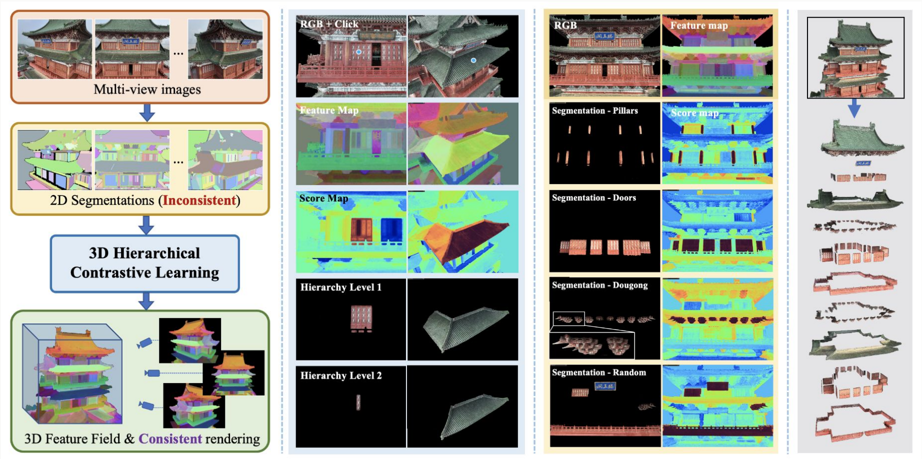
GEOMETRY IN MACHINE LEARNING (GML) GROUP

INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

GML1. Segmentation on 3DGS I (Seminar)

3D Gaussian Splatting (3DGS)?

Segmentation on 3DGS via Contrastive learning



B PG ✗
M Sem ✓
M Lab ✗

 OmniSeg3D. Haiyang Ying, el al. 2024 CVPR

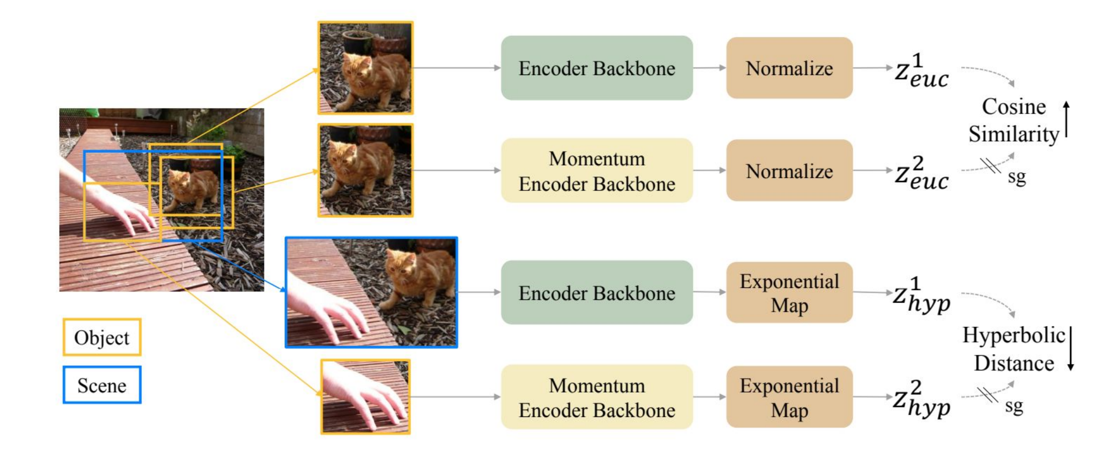
GML1. Segmentation on 3DGS I (Lab course/BPG)

Goal: Integrate Hyperbolic learning into 3DGS Segmentation

Hyperbolic learning?

Euclidean space -> Hyperbolic space(where learning happens)

✅ Hierarchical structure

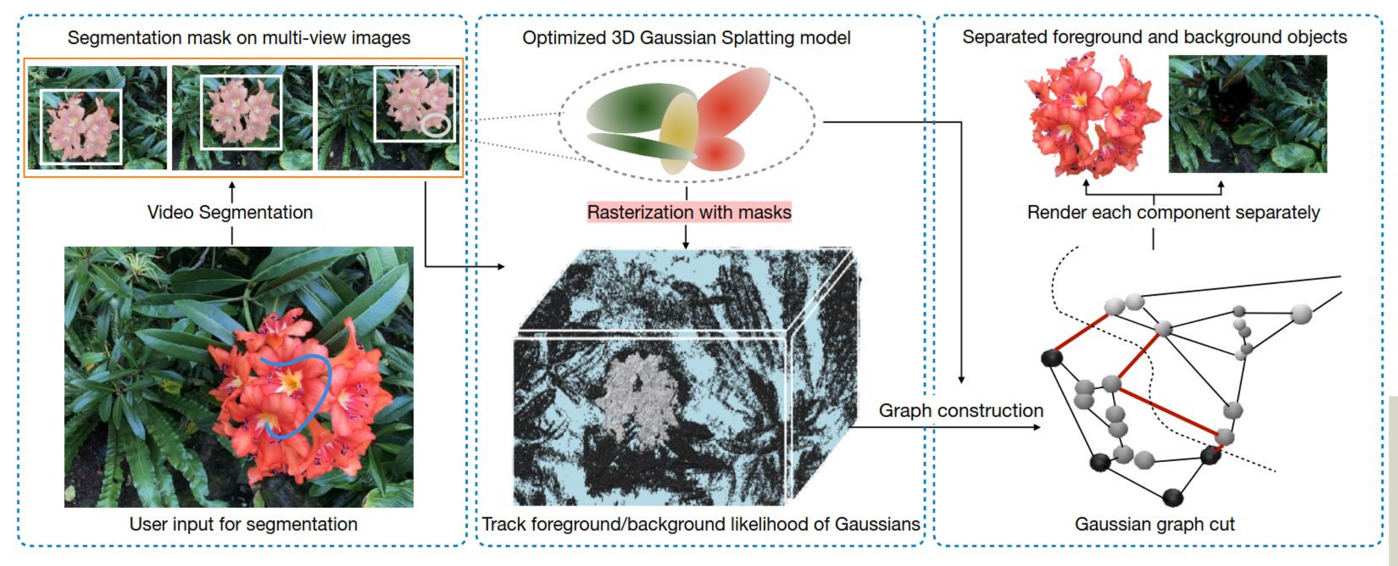


Hyperbolic Contrastive Learning for Visual Representations beyond Objects, Songwei Ge el al. CVPR 2023

B PG ✓
M Sem ✗
M Lab ✓

GML2. Segmentation on 3DGS II (Seminar)

Foreground-background segmentation by minimum-cut algorithm



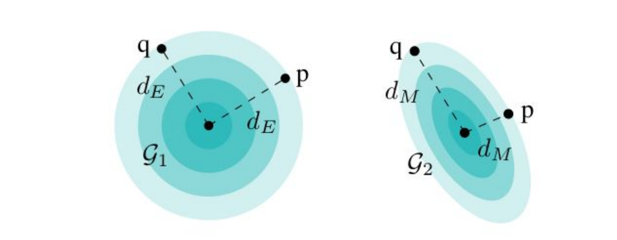
- B PG ✗
- M Sem ✓
- M Lab ✗

GaussianCut: Interactive Segmentation via Graph Cut for 3D Gaussian Splatting, Umangi Jain el al. Neurips2024

GML2. Segmentation on 3DGS II (Lab course/BPG)

Goal 1: Substitute the cost computation

- ➤ Euclidean distance -> Mahalanobis distance



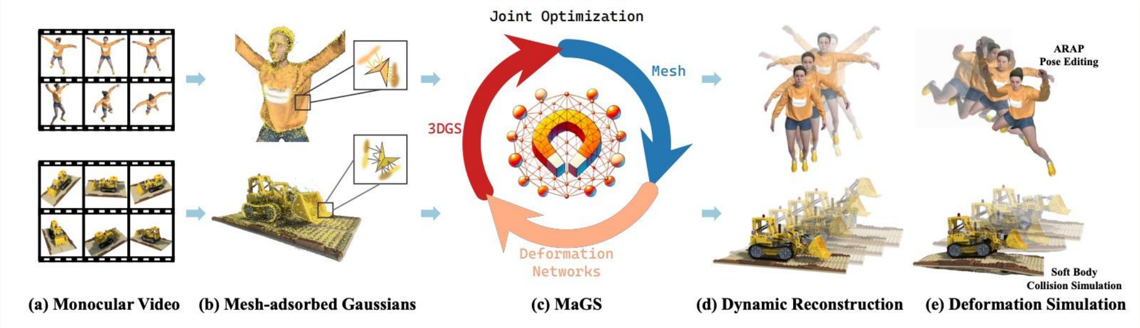
Goal 2: Evaluate its robustness on the quality of 2D Segmentation

- ➤ Randomly remove detected masks
- ➤ Reduce the number of images for segmentation

Goal 3: Virtual camera for more masks, in an interactive way, when lack of views.

B PG ✓
M Sem ✗
M Lab ✓

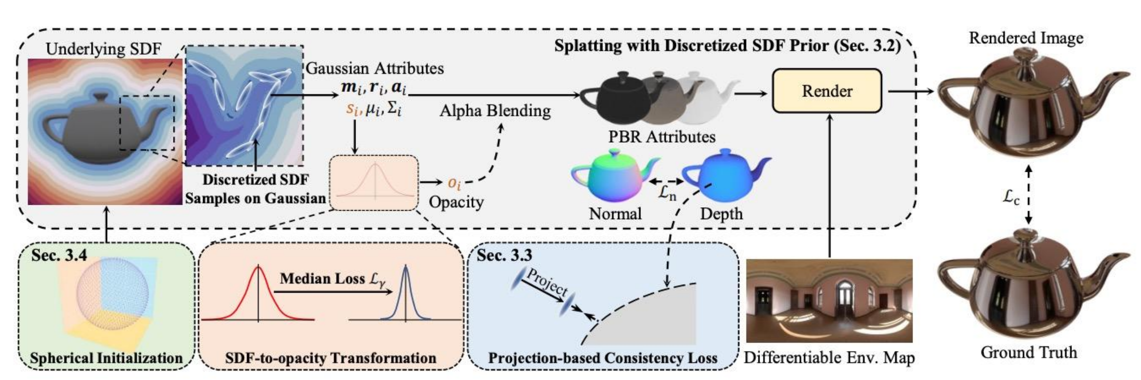
GML3. Dynamic Scene Reconstruction

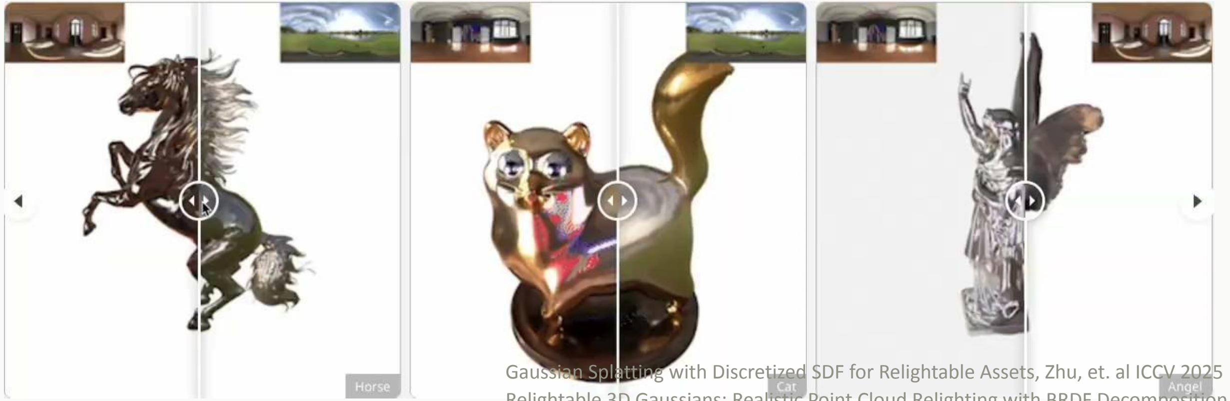


GauSTAR: Gaussian Surface Tracking and Reconstruction, Zheng et. al CVPR 2025
MaGS: Reconstructing and Simulating Dynamic 3D Objects with Mesh-adsorbed Gaussian Splatting, Ma. et. al ICCV 2025

B PG ✗
M Sem ✓
M Lab ✗

GML4. Inverse Rendering on 3D Gaussians





Gaussian Splatting with Discretized SDF for Relightable Assets, Zhu, et. al ICCV 2025
Relightable 3D Gaussians: Realistic Point Cloud Relighting with BRDF Decomposition and Ray Tracing, Cao, et. al ECCV 2024

B PG ✗
M Sem ✓
M Lab ✗

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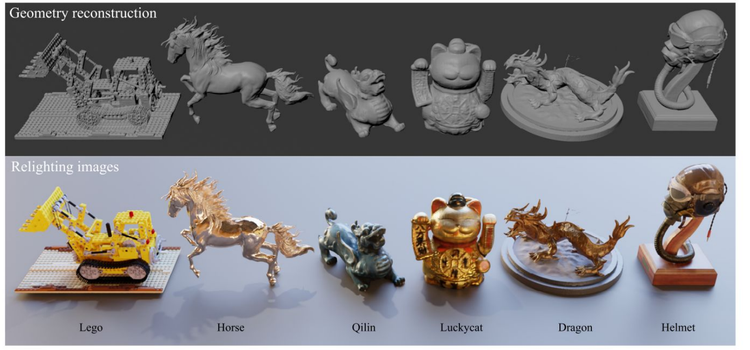
GML4. Inverse Rendering with Material Priors



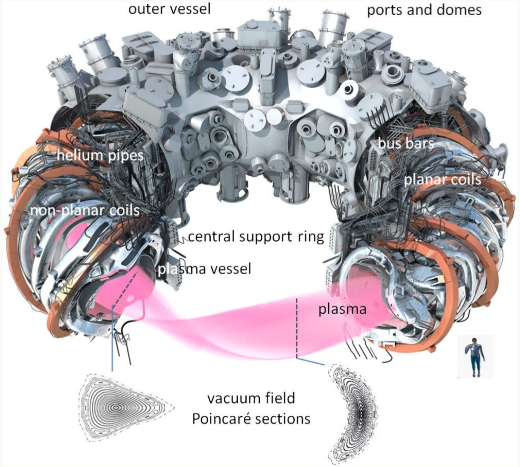
- Extending the baseline to indoor scenes.
- Material and lighting initialization using Material Diffusion Model.
- Experiment how this affects the quality of geometry, material and lighting in inverse rendering.

TensoSDF: Roughness-aware Tensorial Representation for Robust Geometry and Material Reconstruction, Li, et. al Siggraph 2024
Intrinsic Image Diffusion for Indoor Single-view Material Estimation, Kocsis, et. al. CVPR 2024

B PG
M Sem
M Lab

GML5. Fusion Energy Generation (BPG/Lab/Seminar)

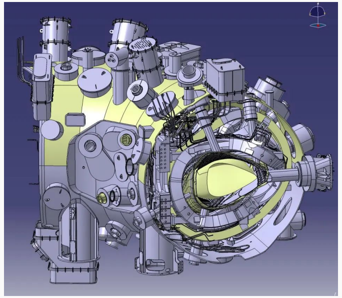
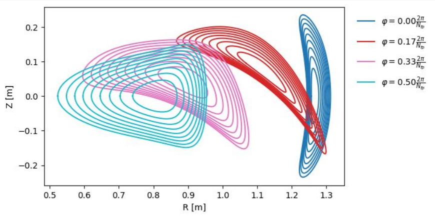
- Goal: safe and sustainable energy with fusion energy generation
- Requires plasma state (hot and high pressure)
- Current prototypes are not yet efficient enough

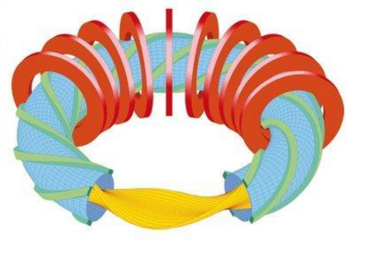
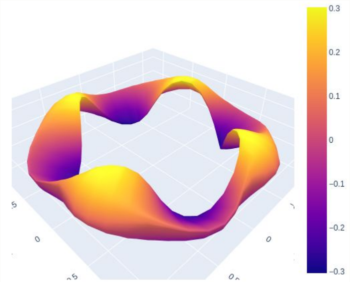


MPI for Plasma Physics

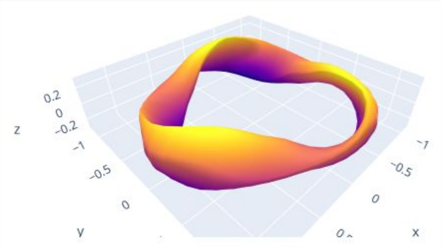
Stellarator - Plasma Shape Optimization

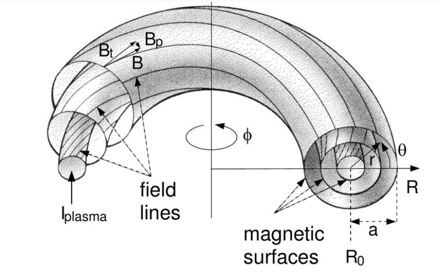
- Stellarator: fusion generator type for continuous operation (But more complex shape)
- Based on magnetic confinement
- Challenge: Many parameters to optimize (stability, magnetic field properties, coil shape, …)

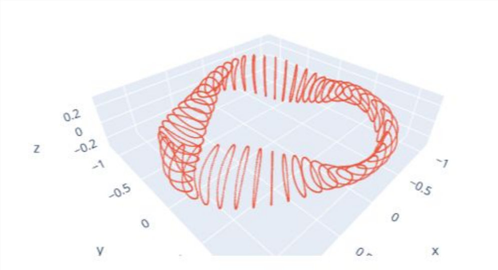



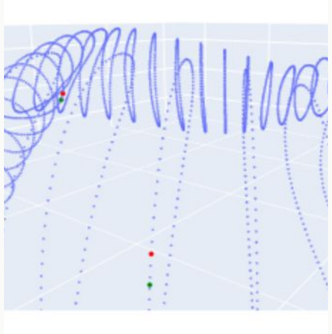



Task 1: Plasma Shape Representations







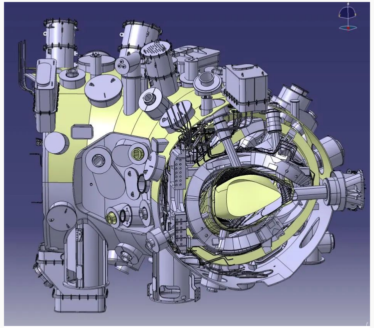


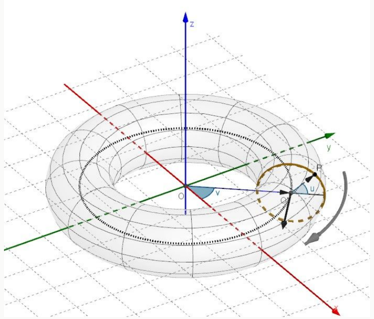
- Standard: Fourier Representation based on toroidal angles
- Convert between other representation such as meshes

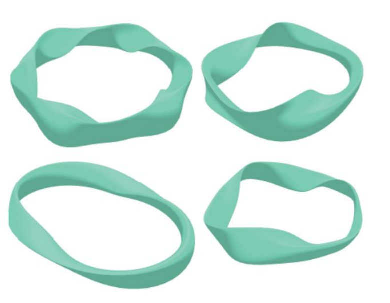
This project is affected by embargo restrictions.

B PG ✓
M Sem ✗
M Lab ✓

Task 2: Design Tool Development





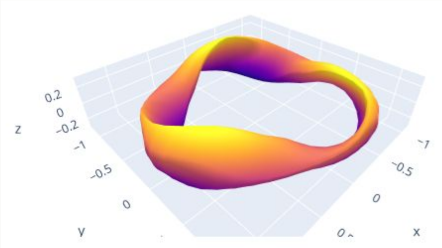


- Goal: quick parameter feedback for small engineering-related changes
- Build editing tool (Python)
- Estimate closest plasma shape from database (full simulation is time-consuming)

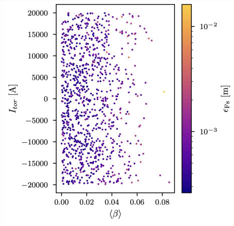
This project is affected by embargo restrictions.

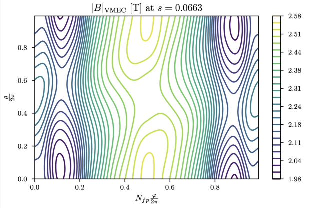
B PG ✓
M Sem ✗
M Lab ✓

Task 3: Neural Surrogate Development



But fast!





- Surrogate models allow us to quickly get approximate simulation results
- How to use Physics-Knowledge to improve them?

Physics-regularized neural network of the ideal-MHD solution operator in Wendelstein 7-X Configurations
Merlo et. al. 2023

This project is affected by embargo restrictions.

B PG
M Sem
M Lab

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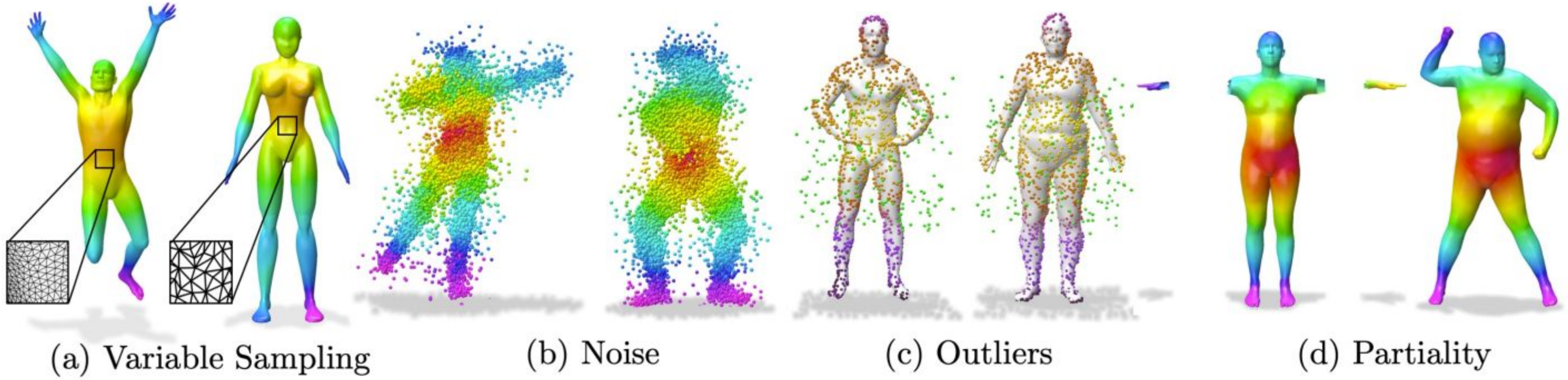
LOVC: IMPLICIT FIELD SUPERVISION FOR ROBUST NON-RIGID SHAPE MATCHING

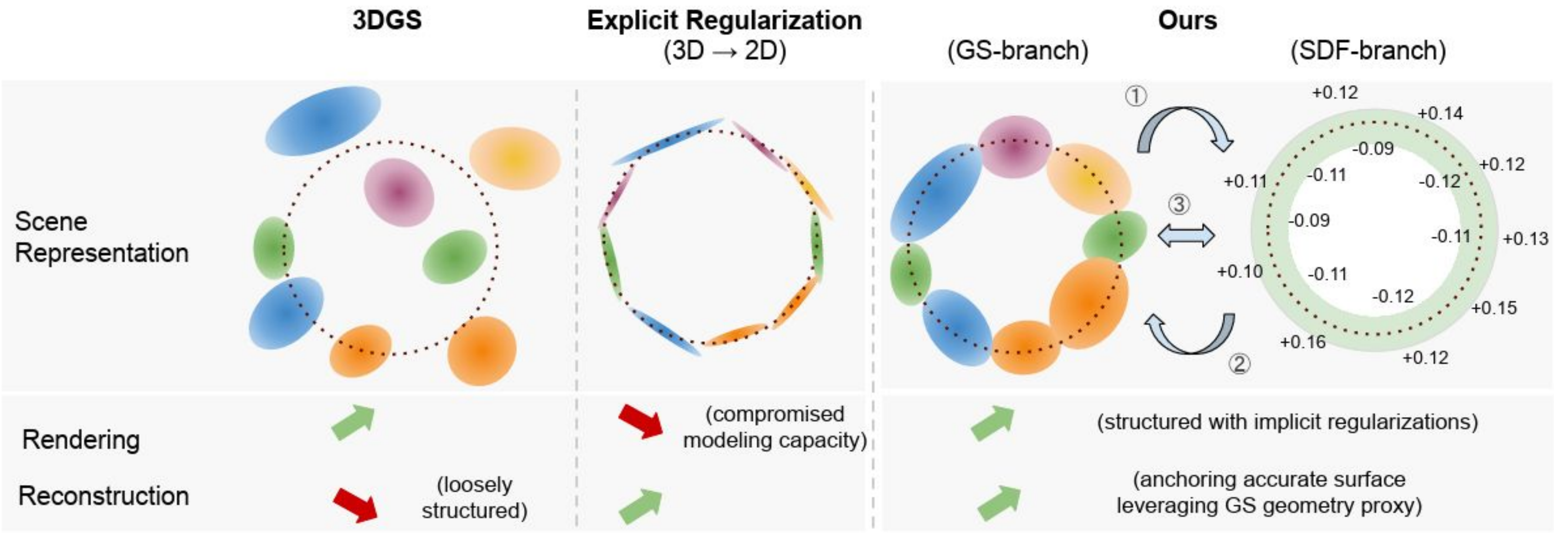


- Fully understand and able to present the core idea of the paper (M Sem)
- Reproduce the results and apply the method on different (animal) dataset (B PG)
- Enable unsupervised training of the method (e.g. via functional map regularisation) (B PG, M Lab)

R.Sundararaman, et al.: Implicit Field Supervision For Robust Non-Rigid Shape Matching (ECCV 2022)

B PG ✓
M Sem ✓
M Lab ✓

LOVC: 3DGS Meets SDF for Improved Neural Rendering and Reconstruction

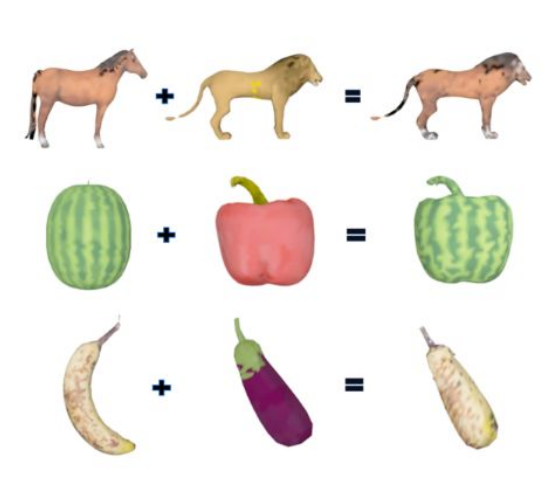


- Fully understand and able to present the core idea of the paper (M Sem)
- Reproduce the results and apply the method on indoor/outdoor datasets (B PG)
- Improve the training speed and get rid of the SfM initialization (B PG, M Lab)

Mulin Yu, et al.: GSDF: 3DGS Meets SDF for Improved Neural Rendering and Reconstruction (NeurIPS 2024)

B PG ✓
M Sem ✓
M Lab ✓

LOVC: DenseMatcher Banana: Learning 3D Semantic Correspondence for Category-Level Manipulation from One Demo



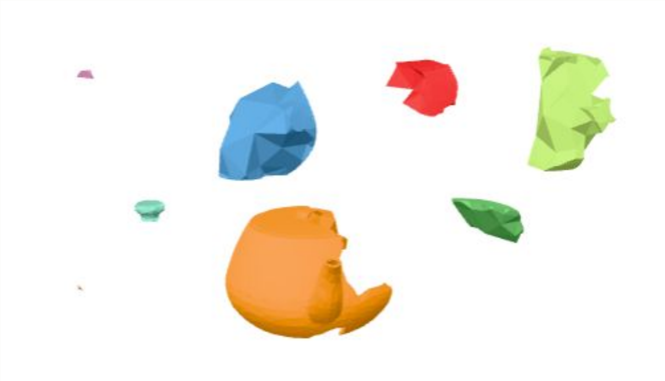
- DenseMatcher estiamtes dense 3D correspondences using 2D foundation model backbones and functional maps,
- It uses part labels as a soft supervision during training.

- Fully understand and be able to present the core idea of the paper. (M Sem)
- Reproduce the results and apply the method to new unseen categories and evaluate its performance. (B PG)
- Integrate an unsupervised soft label predictor (semantic matching) to avoid the need for the part labels for training (B PG, M Lab)

B PG ✓
M Sem ✓
M Lab ✓

Zhu, et al.: DenseMatcher Banana: Learning 3D Semantic Correspondence for Category-Level Manipulation from One Demo (ICLR 2025)

LOVC: Assembling 3D Fractured Shapes



B PG ✓
M Sem ✓
M Lab ✓

Sellán, Silvia, et al. "Breaking bad: A dataset for geometric fracture and reassembly." NeurIPS (2022)

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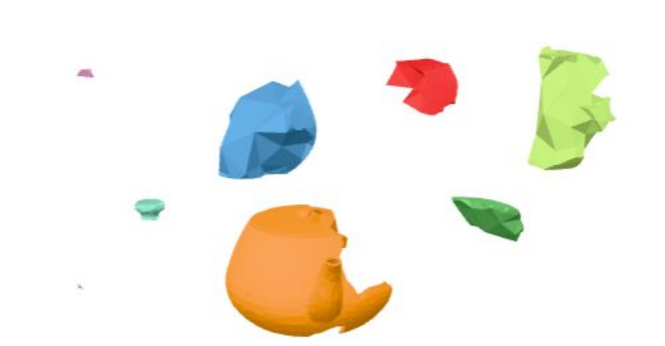
LOVC: Assembling 3D Fractured Shapes



Assembly of fractured objects is an important task in artefact preservation, robotics, geometrcy processing and beyond. **Fracture assembly essentially boils down to finding a matching between boundaries of shattered parts.** Recent shape matching methods can be extended for fracture assembly as they are based on matching boundaries.

Read/understand/summarise paper by Sellán et al. and Roetzer et al. (MSem)
+ run recent fracture assembly method and shape matching method locally (BPG)
+ derive an integer linear programming formalism based on Roetzer et al. For fracture assembly

B PG ✓
M Sem ✓
M Lab ✓

Roetzer, Paul, et al. "Fast Globally Optimal and Geometrically Consistent 3D Shape Matching." Arxiv (2025)
Sellán, Silvia, et al. "Breaking bad: A dataset for geometric fracture and reassembly." NeurIPS (2022)

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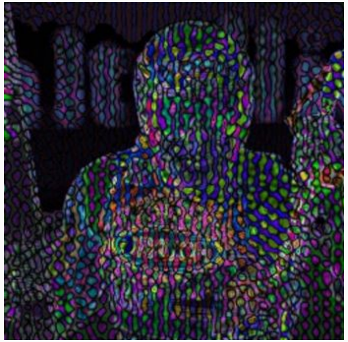
LOVC: Mask Image Watermarking

Original

+



Residual

=

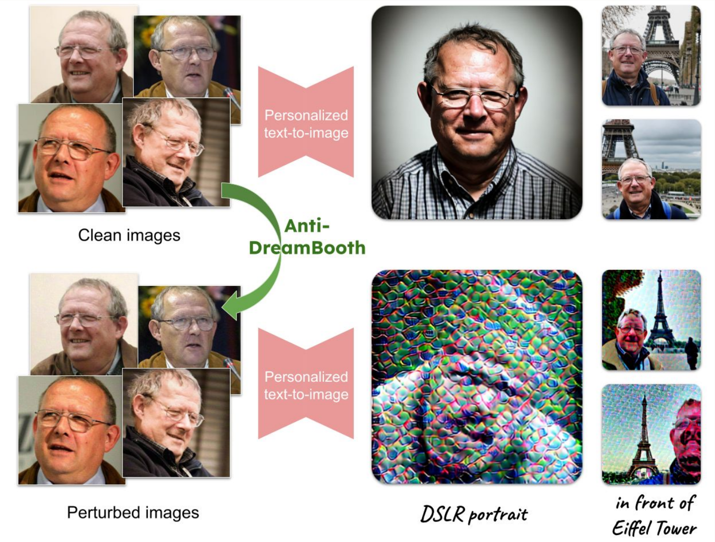
Watermarked

- ❑ Fully understand and able to present the core idea of the paper (M Sem)
- ❑ Run official code implementation and evaluate on diffusion-based purification attacks (B PG)
- ❑ Improve drawbacks (e.g. robustness to crop&resize; diffusion-based purification) and/or explore novel applications (e.g. detection of watermark on faceswapped images) (B PG, M Lab/Thesis)

📜 Runyi Hu, et al.: *Mask Image Watermarking* (NeurIPS 2025)

B PG ✓
M Sem ✓
M Lab ✓

LOVC: Anti-DreamBooth: Protecting users from personalized text-to-image synthesis



- ❑ Fully understand and able to present the core idea of the paper (M Sem)
- ❑ Run official code implementation and implement targetted attacks (B PG)
- ❑ Improve drawbacks (e.g. robustness to diffusion-based purification) and/or explore other applications (e.g. combination with watermarking; defense against faceswap) (B PG, M Lab/Thesis)

B PG ✓
M Sem ✓
M Lab ✓

📜 Thanh Van Le, et al.: *Anti-DreamBooth: Protecting users from personalized text-to-image synthesis* (ICCV 2023)

LOVC: Unsupervised Keypoints from Pretrained Diffusion Models

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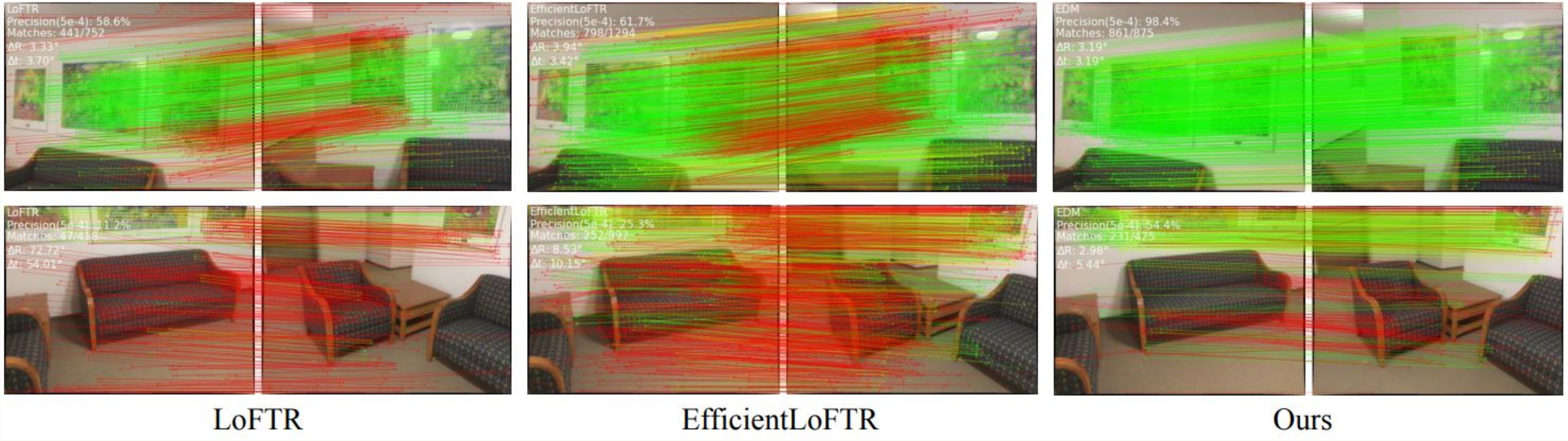
- Understand the core idea of the paper. (B PG, M Sem, M Lab)
- Run official code implementation on other datasets and find possible drawbacks of this method. (B PG, M Lab)
- Improve drawbacks of this paper: (1) it lacks modelling of invisible/occluded keypoints; (2) it cannot distinguish between similar structures (e.g., left/right feet). (M Lab)

B PG ✓
M Sem ✓
M Lab ✓

Hedlin, Eric, et al. "Unsupervised keypoints from pretrained diffusion models." CVPR. 2024.

EDM: Efficient Deep Feature Matching



- Understand the core idea of the paper. (B PG, M Sem, M Lab)
- Run official code implementation on other datasets and find possible drawbacks of this method. (B PG, M Lab)
- Improve some limitations (M Lab) :
  - ✔ (a) This method is multi-stages, extend it to an end-to-end method.
  - ✔ (b) Similar structures could still lead to incorrect matching.

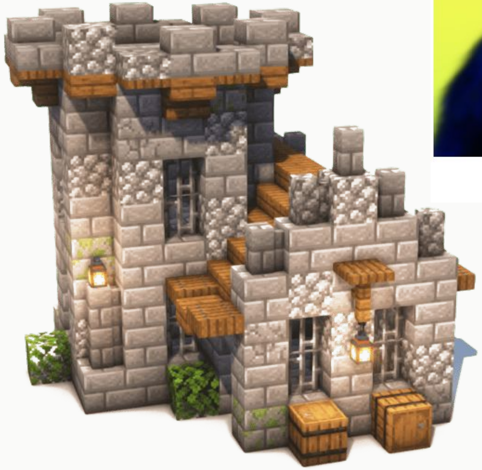
B PG ✓
M Sem ✓
M Lab ✓

Li, Xi, Tong Rao, and Cihui Pan. "EDM: Efficient Deep Feature Matching." ICCV. 2025.

LOVC: Bridging Continuous Generation and Discrete Worlds

a chimpanzee dressed like Henry VIII king of England*

https://builditapp.com/earth-golem/



https://builditapp.com/tiny-castle-2/

Develop methods to apply continuous generation to discrete worlds
(M Lab / Thesis)

B PG
M Sem
M Lab

Poole et al.: DreamFusion: Text-to-3D using 2D Diffusion *(ICLR 2023)*