UNIVERSITÄT BONN

Master Lab, Master Seminar and BACHELOR PROJEKTGRUPPE

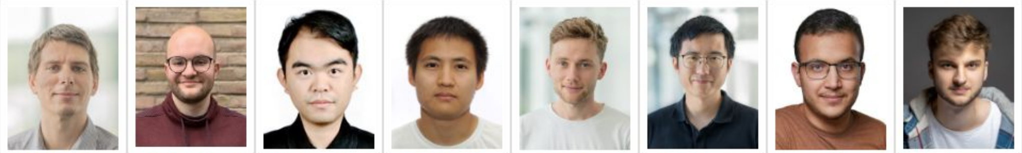
OFFERED BY THE

LOVC, GML & AISD Groups

INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

Groups

LOVC Group (Prof. Dr. Florian Bernard):



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

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

Zorah Lähner	Hongyu Zhou	Lio Schmitz	Mohamed Ebbed	Ipsit Mantri	Ina Taxis	Daniele Baieri
Head of Group	PhD student	PhD student	PhD student	PhD student	PhD student	Postdoc

AI aided Scientific Discovery Group (Prof. Dr. Vahid Babaei):

Pr. Dr. Vahid Babaei — Emiliano Luci — Kevin Tirta Wijaya — Jiahong Wang

Schedule

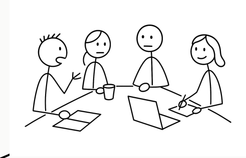
1. General rules for Bachelor Projektgruppe/Master Lab/Master Seminar

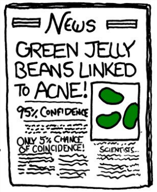
2. 16 Topics for Bachelor Projektgruppe/Master Lab/Master Seminar
   offered by Learning and Optimisation for Visual Computing Group (LOVC)

3. 4 Topics for Master Lab
   offered by AI aided Scientific Discovery Group (AISDG)

4. 9 Topics for Bachelor Projektgruppe/Master Lab/Master Seminar
   offered by Geometry in Machine Learning Group (GML)

Timeline





Choose topics
Topics assigned
Working on Project
Meeting with Supervisors
Presentations
Report due

Today
17.04.2026
21.04.2026
tba
tba
1 week after presentation

Overview

Workload:

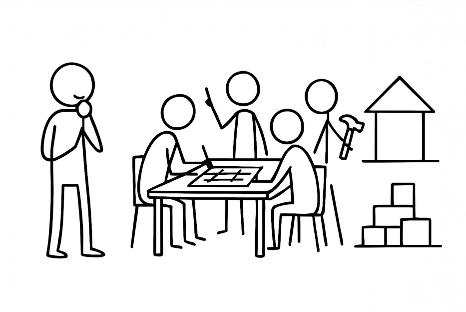
- Literature reading (Seminar, MLab, BPG)
- Implementation (MLab, BPG)

Grading:

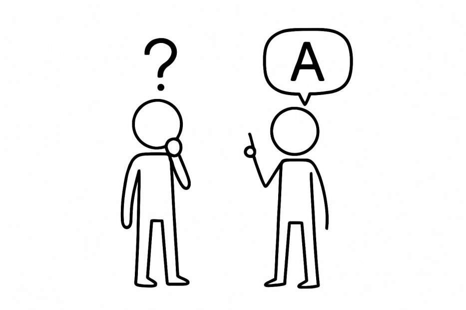
- Presentation
- Report

Supervision

Milestones setting



Meeting (usually weekly)



Answering questions

Presentation practice

Presentation

- Present your work at the end of the semester:

  20mins talk + 5mins 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.

    BPG & M Lab (around **10** pages) and **M Sem** (around **5** 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

Report (NEW)

- Only for Master Seminar.
- It is possible to write the report as a blog post.
- The blog can:
  - Be published online (voluntarily).
  - Should be roughly equivalent to around 5 PDF pages.

Embargo restrictions (MLab Only)

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 - 17.04.2026)

- 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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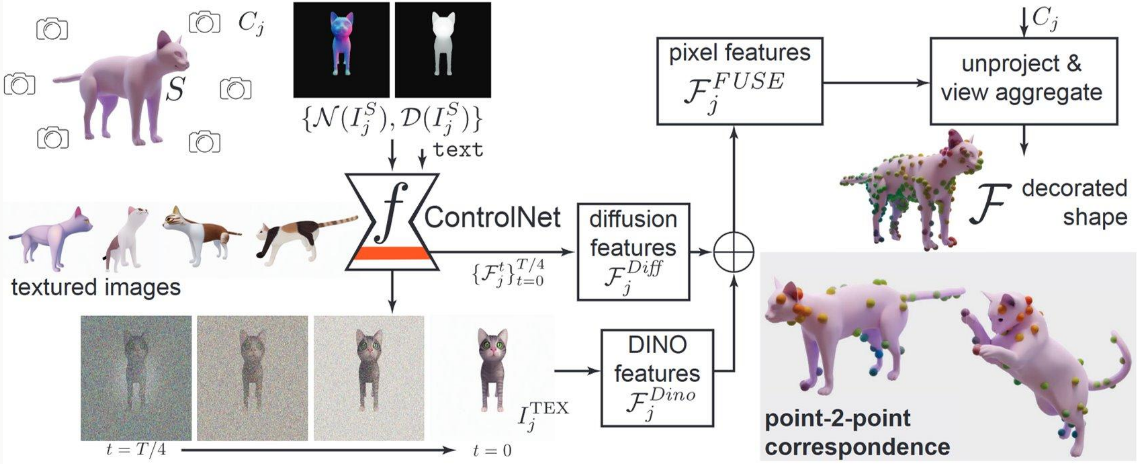
Learning and Optimisation
for Visual Computing (LOVC) GROUP

INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

LOVC1: From Images to Geometry and Back

- Geometry descriptors can be obtained by rendering the geometry and applying a texture using diffusion models
- Feeding these features through ViTs returns a image features which are reprojected onto the geometry
- What if we already know, what the object looks like from a reference image? Can we use this reference to steer the diffusion process and obtain more accurate features?
- **Goal**: Explore and implement diffusion priors based on image inputs

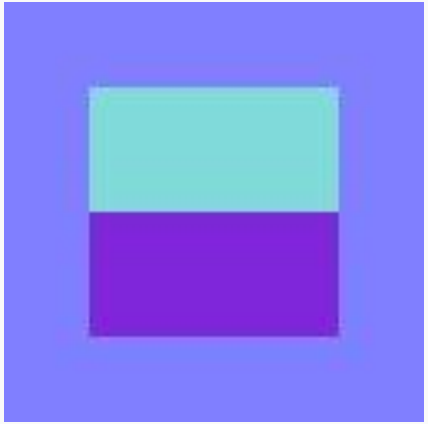


Dutt et al. *Diffusion 3D Features (Diff3F): Decorating Untextured Shapes with Distilled Semantic Features.* (CVPR, 2024)

B PG ✓
M Sem ✓
M Lab ✓

LOVC2: Multigrid Solvers for Irregular Image Domains

- Coarse-to-Fine approaches (for image processing tasks) and multigrid solvers (for solving PDEs) are well-established in their respective fields
- Combining both allows for example the reconstruction of a surface from its normals
- Performant solutions to PDEs in the image domain are underexplored
- **Goal**: Investigate multigrid strategies and apply them to irregular image domains

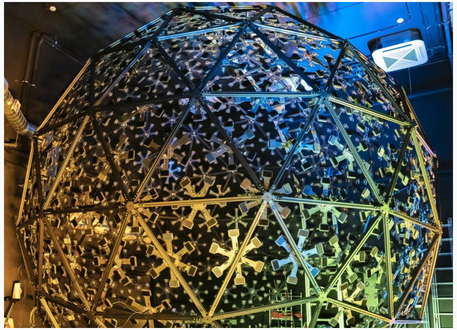


B PG ✓
M Sem ✓
M Lab ✓

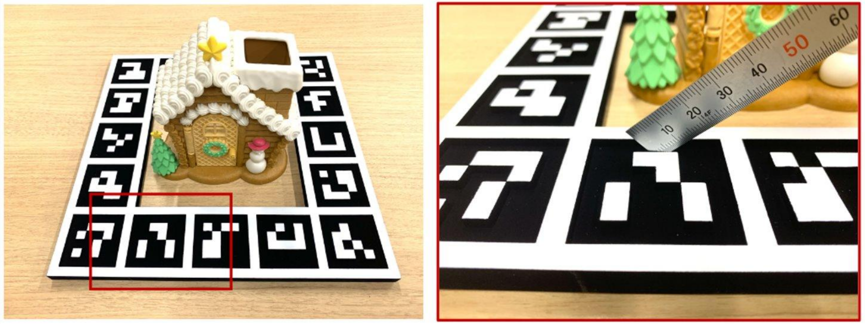
X. Cao, H. Santo, B. Shi, F. Okura, and Y. Matsushita: *Bilateral Normal Integration.* (ECCV, 2022)

LOVC3: One Target to Calibrate them All

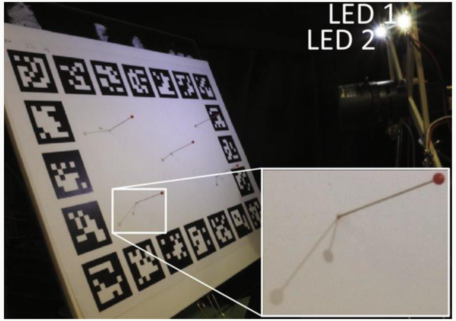
- Modern lightstages combine a multitude of components, e.g. cameras and lights but potentially also laser scanners.
- All these components need to be calibrated (positions, orientations, etc.)
- **Goal**: Combine all these modalities in a single calibration target



Light dome



Camera and laser scanner calibration [2]



Camera Calibration [1]

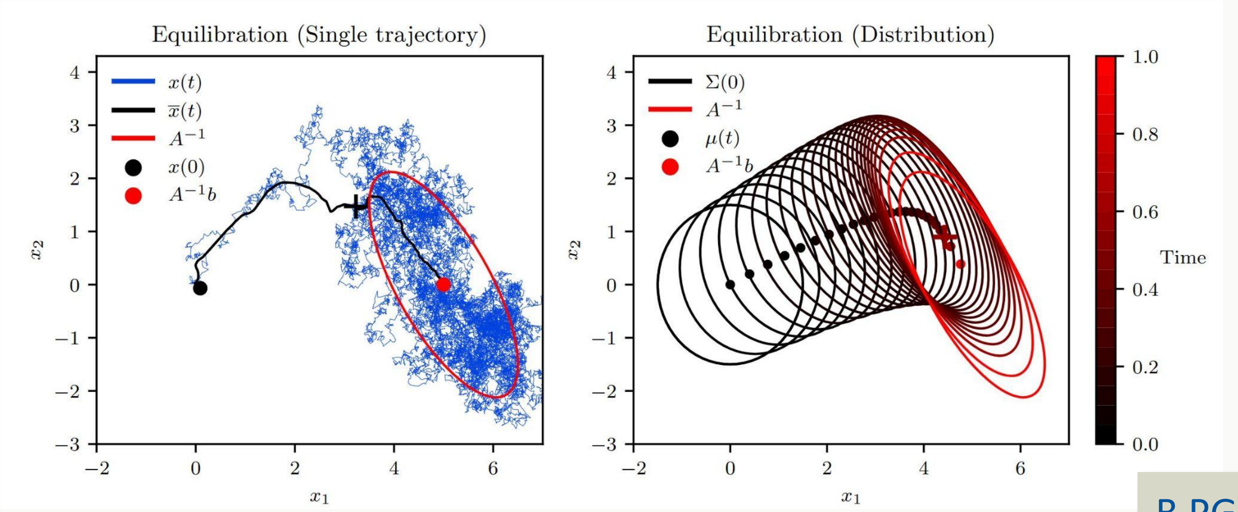
B PG ✓
M Sem ✓
M Lab ✓

[1] H. Santo, M. Waechter, W.-Y. Lin, Y. Sugano and Y. Matsushita: Light Structure from Pin Motion: Geometric Point Light Source Calibration. (IJCV, 2020)
[2] L. Makabe, H. Santo, F. Okura, and Y. Matsushita: Shape-coded aruco: Fiducial marker for bridging 2d and 3d modalities. (WACV, 2022)

LOVC4: Thermodynamic Linear Algebra

- While quantum computing received a lot of attention, thermodynamic computing might be a more feasible approach for the near future.
- The idea is to use thermal fluctuations of a particle to perform various computational tasks

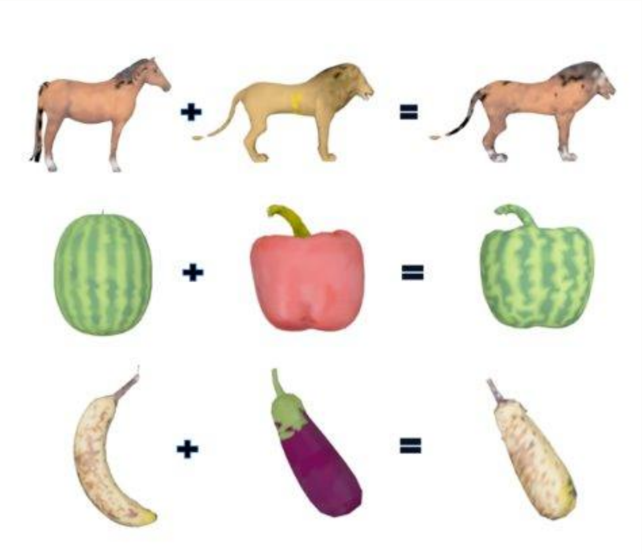
Matrix Solver: $Ax = b$



B PG ✓
M Sem ✓
M Lab ✓

[1] M. Aifer, et al.: Thermodynamic linear algebra. (Unconventional Computing, 2024)

LOVC5: DenseMatcher: Learning 3D Semantic Correspondence



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

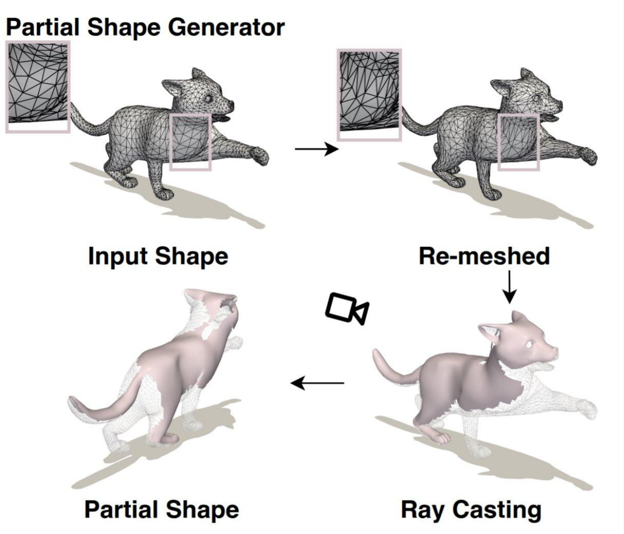
- Fully understand and be able to present the core idea of the paper. (M Sem)
- Reproduce the results and apply the method to new unseen categories and evaluate its performance. (B PG)
- Integrate an unsupervised soft label predictor (semantic matching) to avoid the need for the part labels for training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

LOVC6: Extending BeCoS benchmark

- BeCoS is a benchmark that provides ground truth correspondences between thousands of 3D deformable shapes from multiple categories.



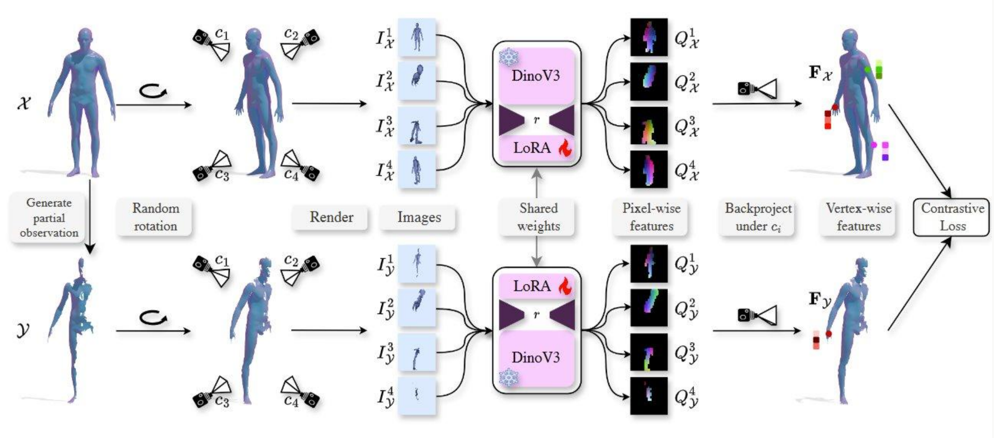
- Reproduce (part of) the results. (B PG, M Lab)

- The results of current shape matching methods on BeCoS are suboptimal. Investigate the reason behind this lack of performance and propose new ways to deal with matching of a highly non-isometric dataset. (B PG, M Lab)

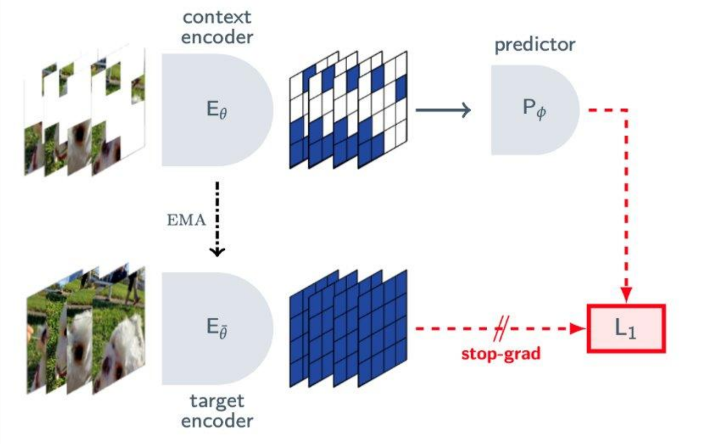
B PG	✓
M Sem	✗
M Lab	✓

Ehm, El Amrani et al.: Beyond Complete Shapes: A Benchmark for Quantitative Evaluationof 3D Shape Surface Matching Algorithms *(SGP 2025)*

LOVC7: Self-Supervised Pre-Training for Robust Non-Rigid 3D Shape Matching



V. Ehm, et al.: Teaching DINOv3 About Partial 3D Geometry: A Self-Supervised Geometry-Aware Approach (CVPR 2026)

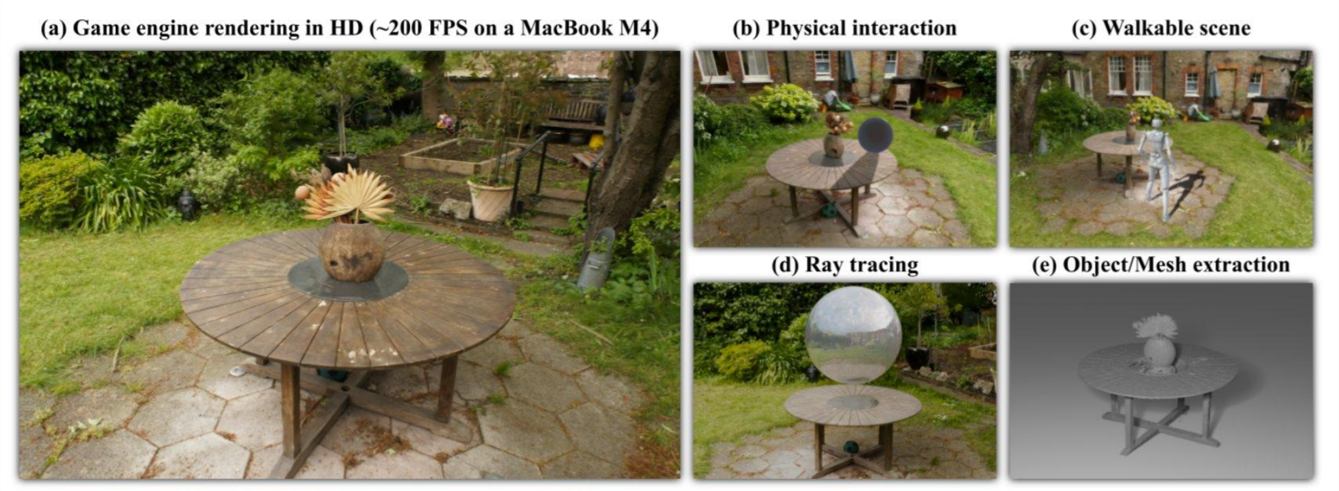


M. Assran, et al.: V-JEPA 2: Self-Supervised Video Models Enable Understanding, Prediction and Planning (arXiv 2025)

- Understand the core idea of the two papers. (B PG, M Sem, M Lab)
- Implement Teaching DINOv3 paper and find possible ways to integrate the idea of JEPA into the pipeline. (B PG, M Lab)
- Extend the idea of JEPA to improve the performance of self-supervised pre-training for non-rigid 3D shape matching (M Lab)

B PG
M Sem
M Lab

LOVC8: MeshSplatting: Differentiable Rendering with Opaque Meshes



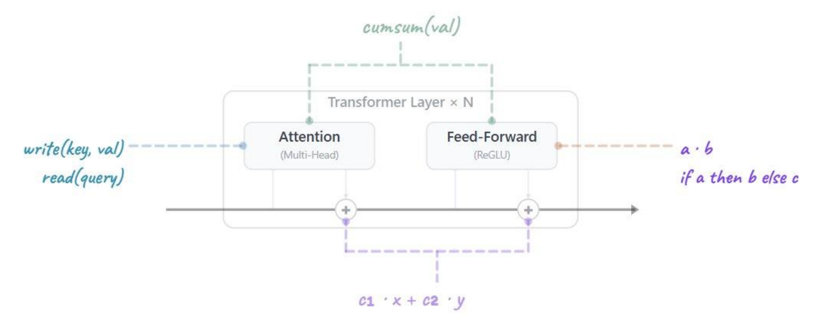
J. Held, et al.: MeshSplatting: Differentiable Rendering with Opaque Meshes (CVPR 2026)

- Understand the core idea of the two papers. (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 the proposed method in terms of mesh reconstruction quality or image rendering quality or training speed (M Lab)

B PG ✓
M Sem ✓
M Lab ✓

LOVC9: Transformers are Computers

- Can Transformer architecture simulate a universal computer?
- Turns out, yes! It can even be realized in weights!
- Their computation model is Append-only Lookup Machine (ALM)



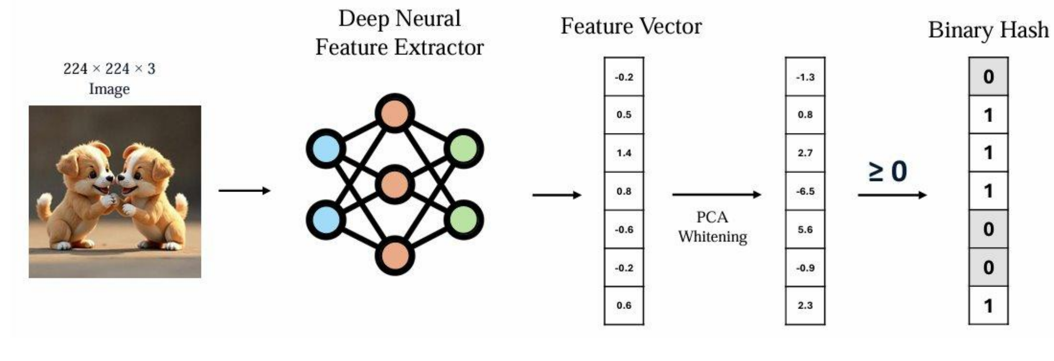
- M Sem: explain the computational model, how operations are encoded into weights, compare to RAM. Prepare report, presentation.
- B PG: run official code, add 1-2 new toy programs, measure runtime/memory/KV-cache, compare compilation choices and programs.
- M Lab: reproduce results, study efficiency and differentiability bottlenecks, extend with one new idea. Write research-style report.

B PG ✓
M Sem ✓
M Lab ✓

[Can LLMs Be Computers? | Percepta](#)
[Constructing an LLM-Computer | Percepta](#)
[Percepta-Core/transformer-vm: Compile programs directly into transformer weights. Includes a 2D convex-hull KV cache with O(log n) inference.](#)

LOVC10: Perceptual Hashes under Semantic AI Edits

- Perceptual hashes are designed to be stable under benign transformations (brightness, contrast, small crop, rotation, scale, compression)
- Useful for near-duplicate matching, retrieval
- Prone to optimizable collision attacks (in contrast to cryptographic hashes)



- M Sem: read CertPHash and 1-2 attack/evaluation papers. Explain certification, evaluation, summarize results. Prepare report, presentation.
- B PG: reproduce baselines, build a small semantic-edit benchmark or diffusion-guided generated benchmark, evaluate baselines.
- M Lab: reproduce baselines, build a semantic-edit benchmark, extend with adversarial and diffusion-guided generative attacks.

B PG ✓
M Sem ✓
M Lab ✓

CertPHasH: Towards Certified Perceptual Hashing via Robust Training. Yang et al. USENIX 2025. Yuchen413/CertPhash
Provenance Detection for AI-Generated Images: Combining Perceptual Hashing, Homomorphic Encryption, and AI Detection Models. Singhi et al. 2025.

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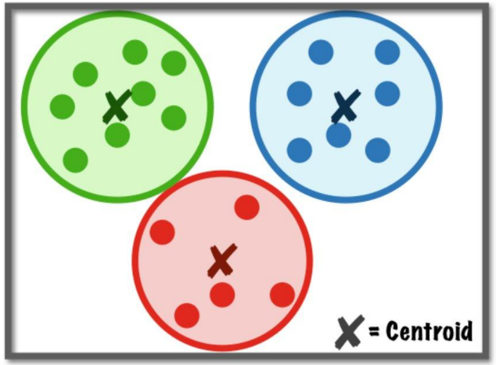
LOVC11: Does perfect Perceptual Hash exist?

- Research Question: Given a finite real-world image dataset and a benign transformation family, when does there exist a perfect perceptual hash that is **invariant within each benign class and separating across all other images**?
- We want to find conditions for Perceptual Hash function $h(\cdot)$ such that it is:

Invariant: if $x \sim y$, then $d\big(h(x), h(y)\big) \leq \tau$, and
Selective: if $x \nsim y$, then $d\big(h(x), h(y)\big) > \tau$.



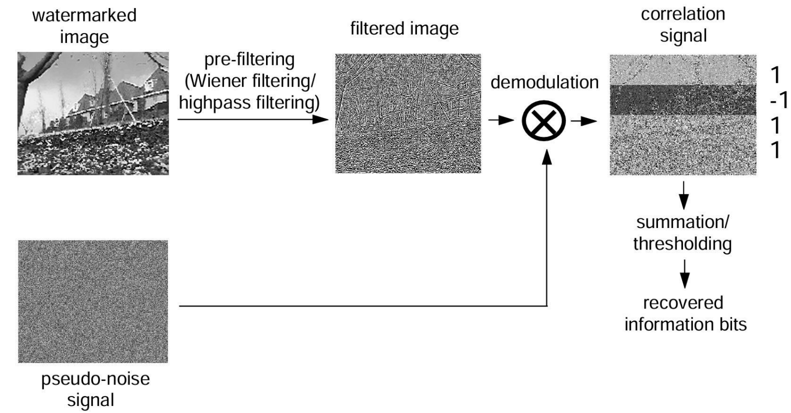
- M Sem: read the literature, formalize the problem, define a perfect perceptual hash, state 1 sufficient condition and 1 impossibility case.
- B PG: reproduce baselines hashes, build a benchmark on different datasets, measure distances, report separability margin.
- M Lab: formalize problem, develop a theory with at least one proposition, validate experimentally. Write research-style report.

B PG ✓
M Sem ✓
M Lab ✓

Robust and secure image hashing. Swaminathan et al. 2006
On Invariance and Selectivity in Representation Learning. Anselmi et al. MIT 2016.

LOVC12: Modernizing Classical Watermarking

- Classical watermarking techniques, like Spread Spectrum, are great! They are fast, simple, imperceptible.
- They lack adaptive robustness to geometric transformations, limited payload support, weaker blind detection.
- Let's modernize them!

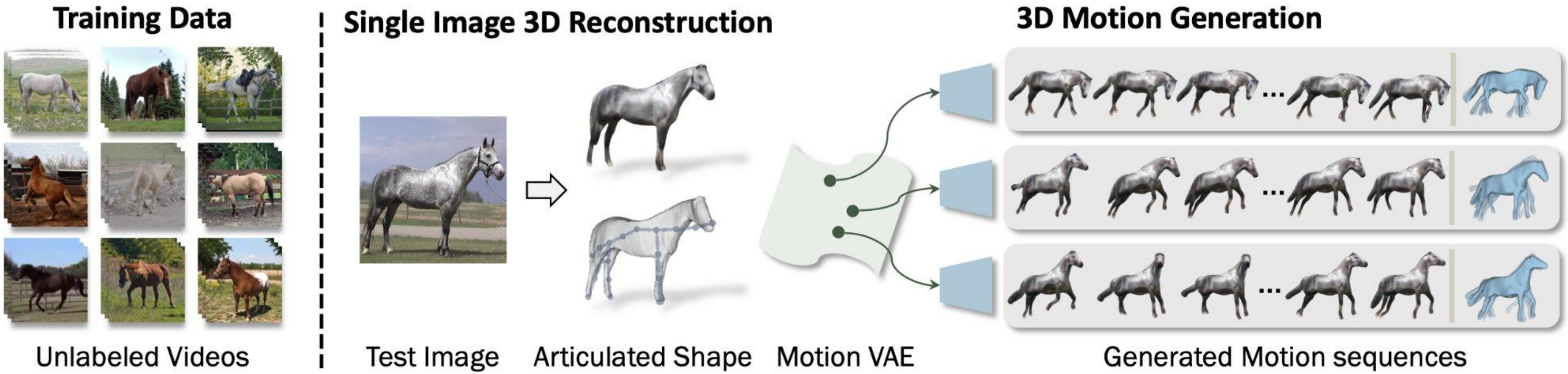


- M Sem: review classical SS / SS-FM watermarking, explain their drawbacks vs modern methods, propose hybrid design.
- B PG: reproduce SS, SS-FM baselines, add payload using ECC, add blind detection with calibrated threshold, speed/robustness study.
- M Lab: reproduce baselines, add payload and blind detection, add one novel robustness mechanism. Write research-style report.

B PG ✓
M Sem ✓
M Lab ✓

Spread Spectrum Watermarking: Malicious Attacks and Counterattacks. Hartung et al. 1999.
Rotation, scale and translation invariant spread spectrum digital image watermarking. Ruanaidh et al. 1998

LOVC13: Ponymation: Learning Articulated 3D Animal Motions from Unlabeled Online Videos

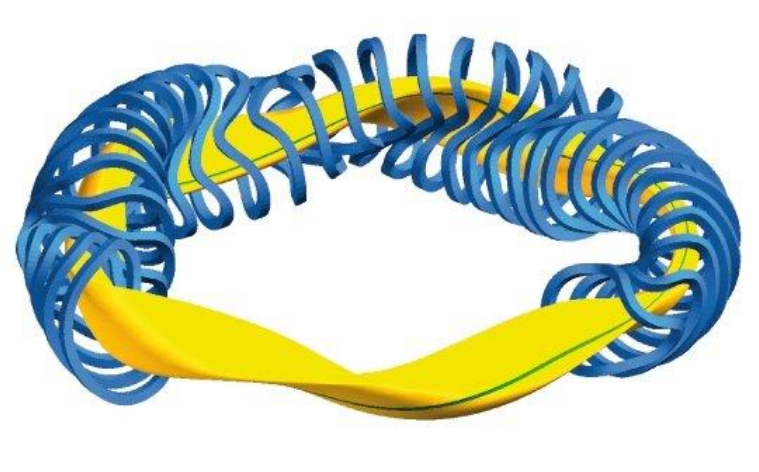


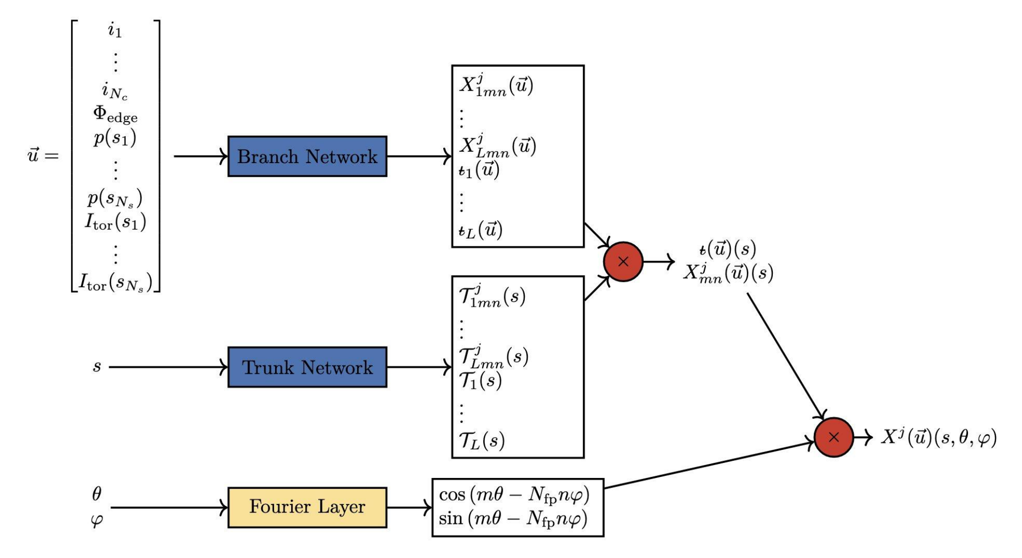
- Understand and present the core idea of the paper. (B PG, M Sem, M Lab)
- Run official code implementation on other datasets and find possible drawbacks of this method. (B PG, M Lab)
- Make the method work on unstructured image data. (M Lab)

B PG ✓
M Sem ✓
M Lab ✓

Li, R., Wu, S., Jakab, T., Rupprecht, C., & Vedaldi, A. (2024). Ponymation: Learning Articulated 3D Animal Motions from Unlabeled Online Videos. ECCV 2024.

LOVC14: Learning surrogate models for stellarator design





- Understand and present the core idea of (1). (M Sem)
- Evaluate different neural network architectures for surrogate modelling for (2) (M Lab, BPG)

B PG ✓
M Sem ✓
M Lab ✓

Merlo, A., et al. (2023). Physics-regularized neural network of the ideal-MHD solution operator in Wendelstein 7-X configurations. Nuclear Fusion, 63, 066020.
Cadena, S. A., Merlo, A., Laude, E., et al. (2025). ConStellaration: A dataset of QI-like stellarator plasma boundaries and optimization benchmarks. NeurIPS 2025. arXiv:2506.19583

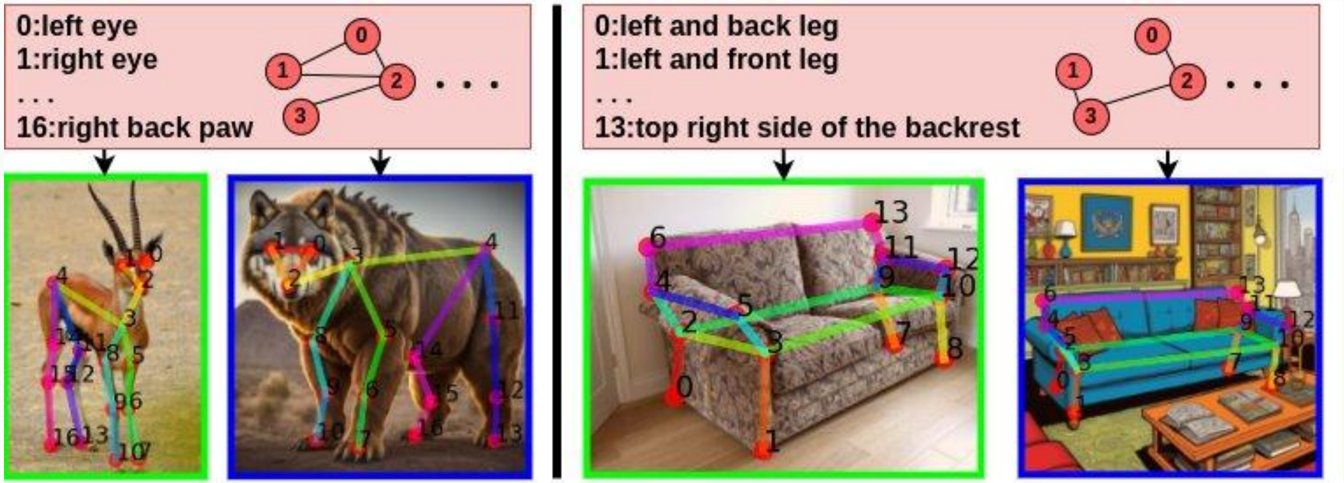
LOVC15: Back to 3D - Few-Shot 3D Keypoint Detection with Back-Projected 2D Features

- 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 possible drawbacks within the pipeline including (1) better semantics, or (2) symmetry-aware. (M Lab)

B PG ✓
M Sem ✓
M Lab ✓

Wimmer, Thomas, Peter Wonka, and Maks Ovsjanikov. "Back to 3d: Few-shot 3d keypoint detection with back-projected 2d features." CVPR 2024

LOVC16: CapeX - Category-Agnostic Pose Estimation from Textual Point Explanation



- 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 possible drawbacks within the pipeline including (1) better feature learning, or (2) alleviating symmetry ambiguity. (M Lab)

B PG ✓
M Sem ✓
M Lab ✓

Wimmer, Thomas, Peter Wonka, and Maks Ovsjanikov. "Back to 3d: Few-shot 3d keypoint detection with back-projected 2d features." CVPR 2024

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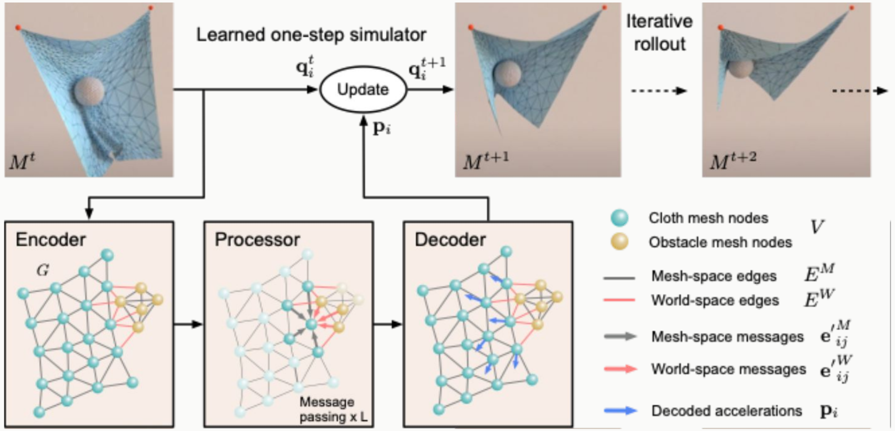
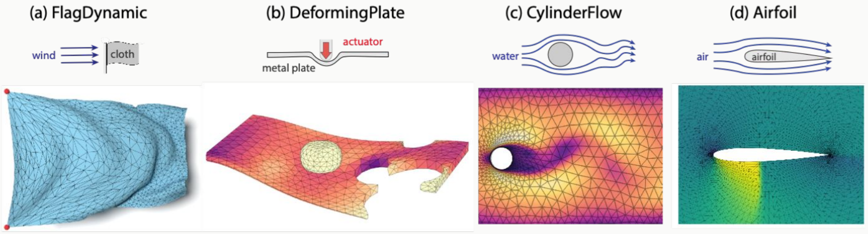
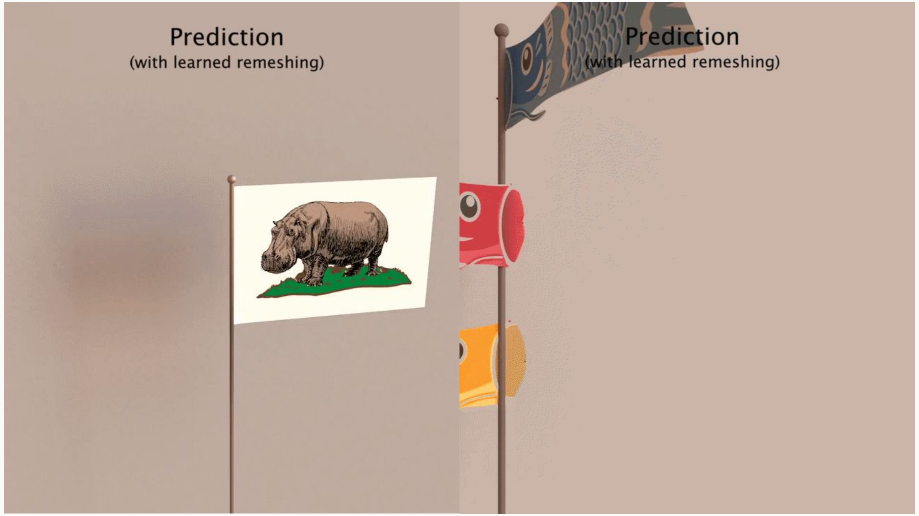
AISDG 1: Mesh-based Neural Surrogate Modeling







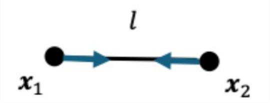
- Goal 1: Extend it to fluid-solid interactions
  - Foundation model for Lagrangian systems

B PG ✗
M Sem ✗
M Lab ✓

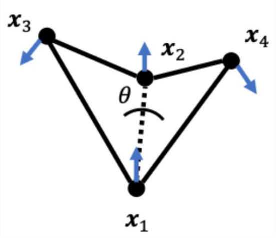
Pfaff, Tobias, et al. “Learning mesh-based simulation with graph networks.” ICLR 2021

AISDG 1: Mesh-based Neural Surrogate Modeling

- Goal 2: Look at per-element formulation



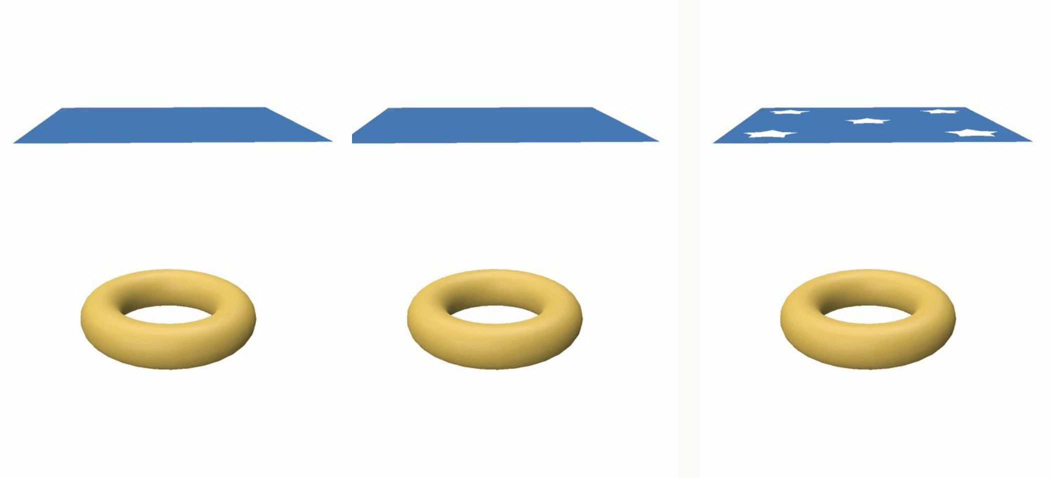
Edge Impulse



Hinge Impulse

Edge impulse --> Edge stress

Auto recover strain-stress constitutive relation



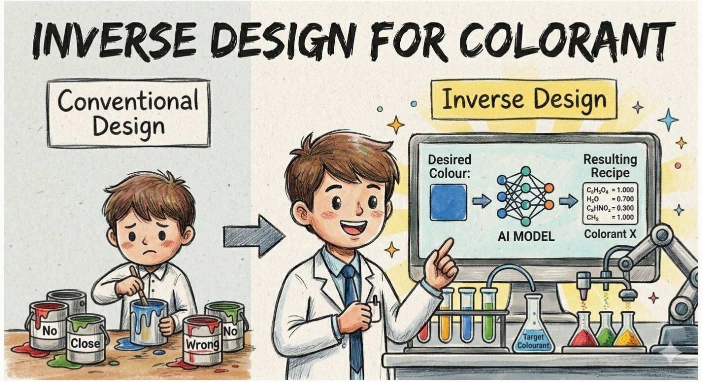
MeshGraphNets | MomentumGNN (ours) | MomentumGNN (star-perforated)

- Goal 3: Investigate constraints
  - Collision-free dynamics
  - Dry frictions

B PG
M Sem
M Lab

Jiahong, Wang, et al. "Momentum-Conserving Graph Neural Networks for Deformable Objects." 3DV 2026

AISDG 2: Inverse Design of Dyes/Pigments

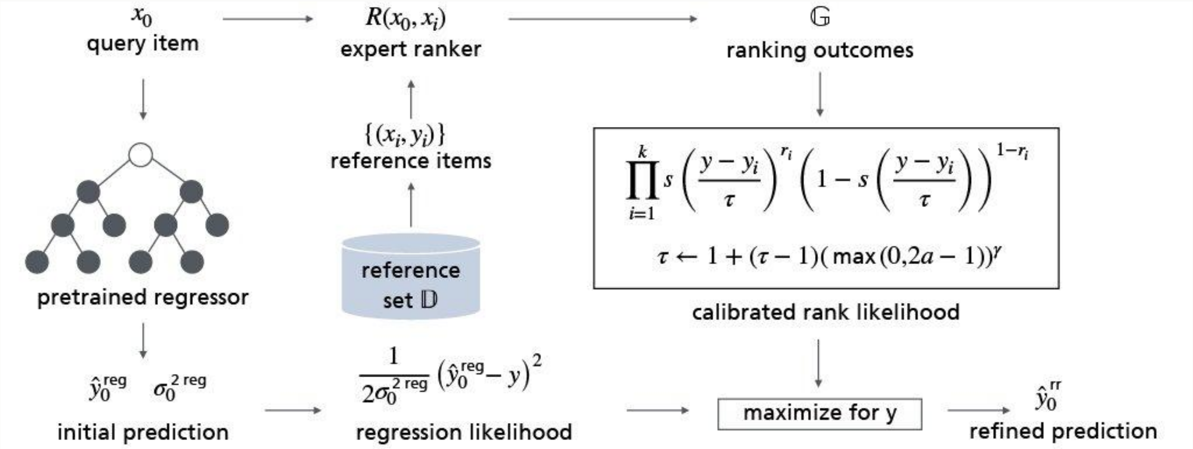


- Build a database of molecule (design) → color (performance) from online sources (e.g., https://www.worlddyevariety.com/)
- Experiment with autoinverse to automatically propose a molecule that will display the desired color
- Validate the proposed design with Density Functional Theory (DFT) software like ORCA (https://orca-manual.mpi-muelheim.mpg.de/)

B PG ✗
M Sem ✗
M Lab ✓

Ansari et al. Autoinverse: Uncertainty Aware Inversion of Neural Networks. NeurIPS 2022.

AISDG 3: Improving Regression Predictions with Rankings



- Extend the idea from pairwise comparisons to listwise comparisons.
- Experiment how systematic ranking bias and different reference sampling strategy affect the performance

B PG	✗
M Sem	✗
M Lab	✓

Ansari et al. Autoinverse: Uncertainty Aware Inversion of Neural Networks. NeurIPS 2022.

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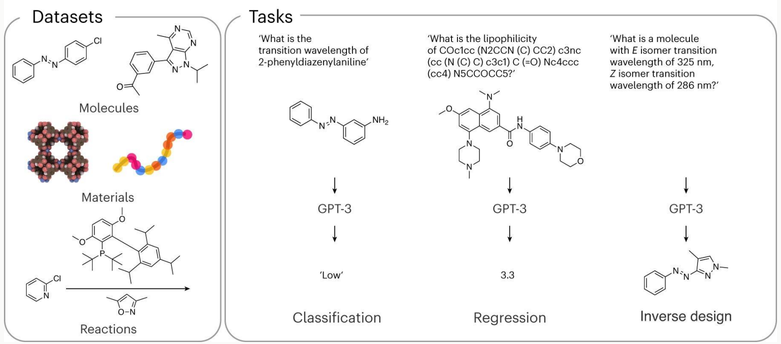
AISDG 4: AI for ranking-based optimization

Bayesian Optimization for Controlled Image Editing via LLMs (Cai et al. ACL 2025)



Leveraging large language models for predictive chemistry (Jablonka et al. Nature 2024)

- Defining an objective function is often very hard. LLMs have proven to be good generalists, especially when combined with in-context learning. Similar to humans, LLMs have also proven to be better at ranking results rather than giving absolute scores. This makes them a natural fit as a substitute for the objective function, rather than computing a score, we ask the LLM to compare candidates and infer preferences from there.

B PG ✗
M Sem ✗
M Lab ✓

Master Lab, Master Seminar
and
BACHELOR PROJEKTGRUPPE

OFFERED BY THE

Geometry in Machine Learning (GML) GROUP

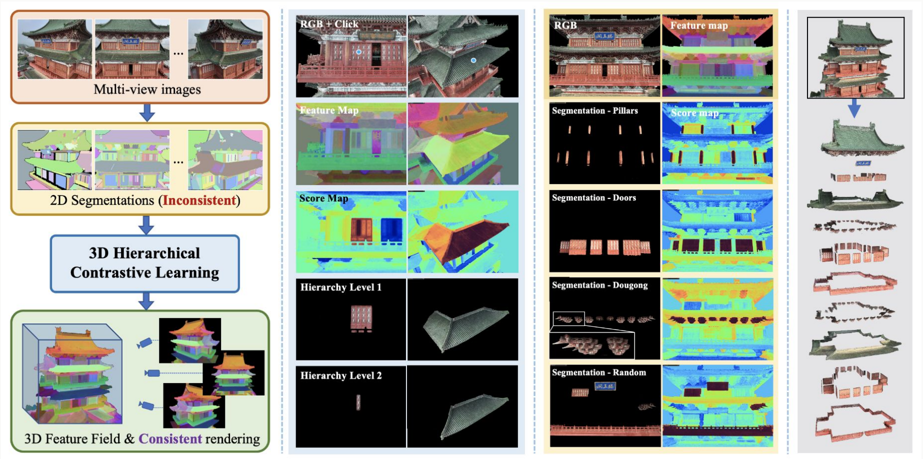
geometryinml.cs.uni-bonn.de

INSTITUTE OF COMPUTER SCIENCE II VISUAL COMPUTING DEPARTMENT

GML1: Segmentation on 3DGS (M Sem)

3D Gaussian Splatting (3DGS)?

Segmentation on 3DGS via Contrastive learning



B PG ✓
M Sem ✓
M Lab ✓

OmniSeg3D. Haiyang Ying, el al. 2024 CVPR

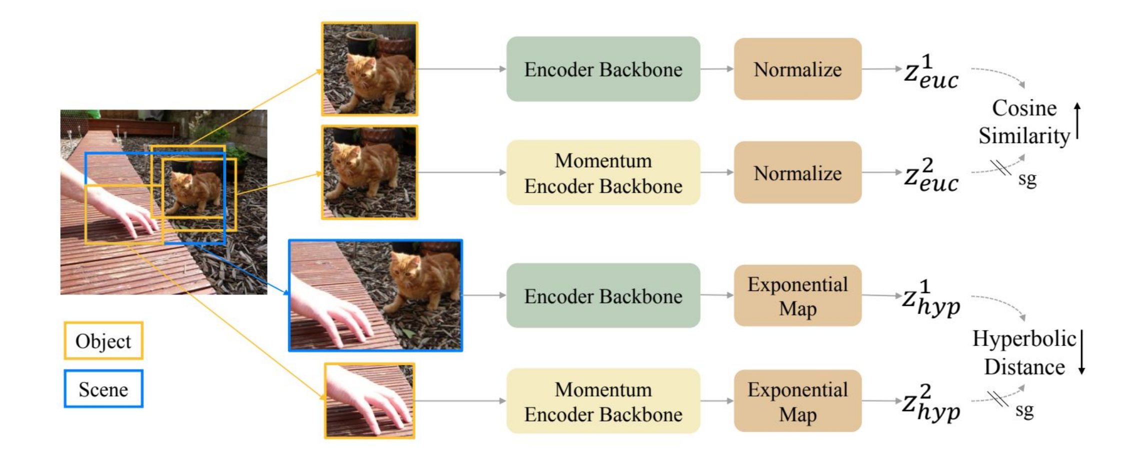
GML1: Segmentation on 3DGS (M Lab/BPG)

Goal: Integrate Hyperbolic learning into 3DGS Segmentation

Hyperbolic learning?

Euclidean space -> Hyperbolic space(where learning happens)

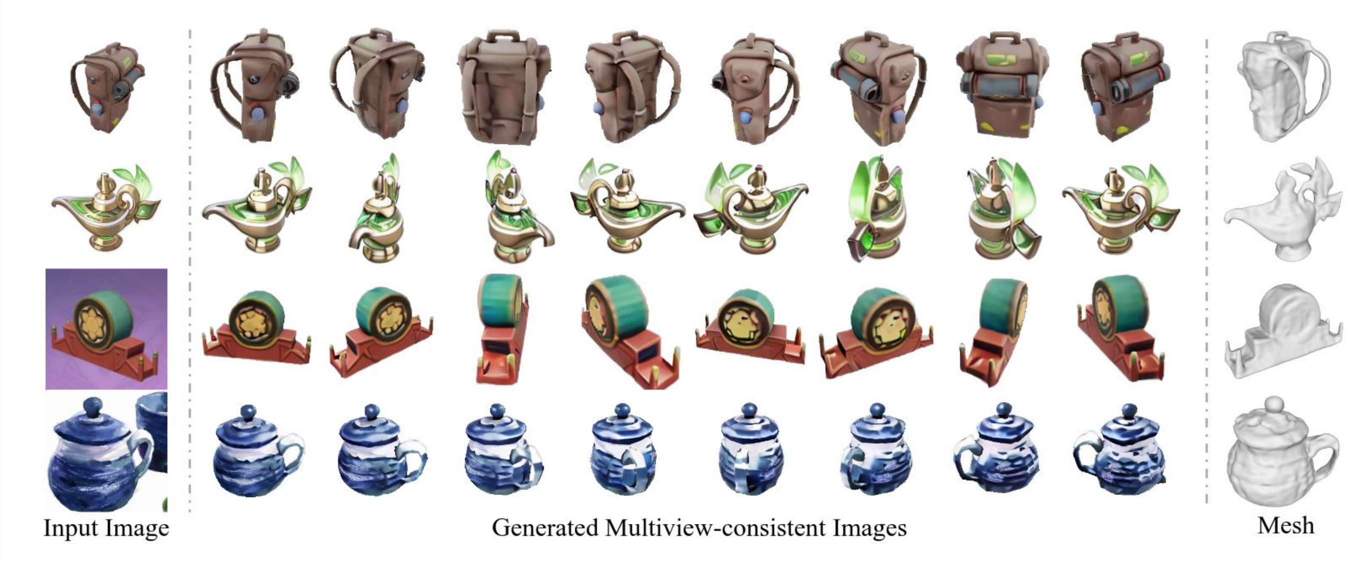
✅ Hierarchical structure



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

B PG ✓
M Sem ✓
M Lab ✓

GML2: Multi-view consistent image generation with 2D diffusion model

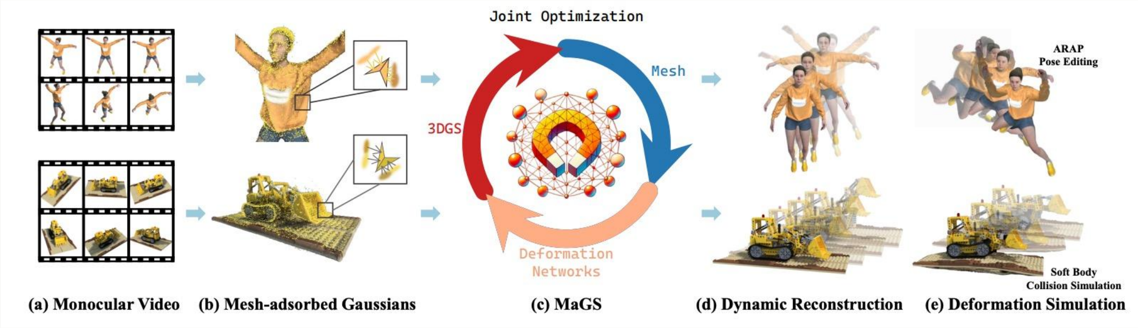


- ❑ Fully understand and able to present the core idea of the paper (M Sem)
- ❑ Reproduce the multiview-consistent image generation part (B PG & M Lab)
- ❑ Do multi-view consistent relighting using the same pipeline (B PG & M Lab)

B PG ✓
M Sem ✓
M Lab ✓

SyncDreamer 2024 ICLR.

GML3: Dynamic Scene Reconstruction



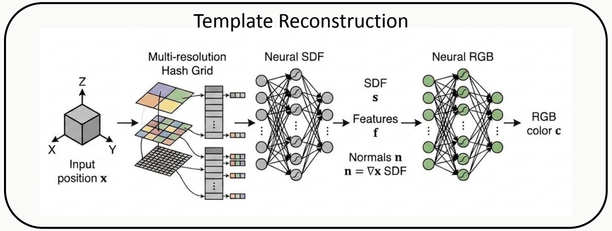
B PG	✗
M Sem	✓
M Lab	✗

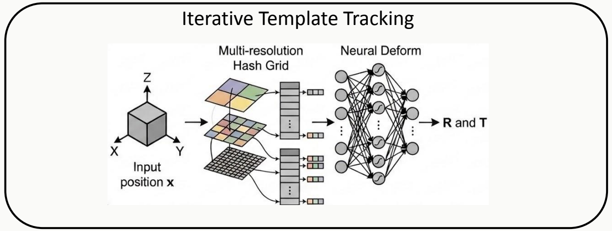
TagSplat: Topology-Aware Gaussian Splatting for Dynamic Mesh Modeling and Tracking, Guo et. al CVPR 2026
GauSTAR: Gaussian Surface Tracking and Reconstruction, Zheng et. al CVPR 2025
MaGS: Reconstructing and Simulating Dynamic 3D Objects with Mesh-adsorbed Gaussian Splatting, Ma et. al ICCV 2025

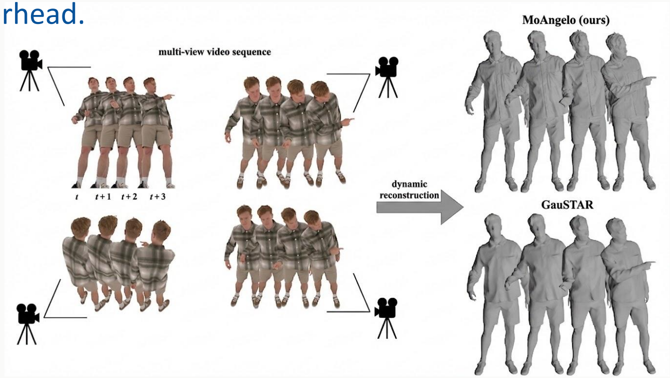
GML3: Dynamic Scene Reconstruction

Project Goals:

- Develop a **memory-efficient 4D scene representation** for dynamic scenes.
- Enable **joint optimization** across frames for improved temporal consistency.
- Overcome limitations of existing approaches:
    - Joint optimization methods suffer from reduced reconstruction quality.
    - Iterative approaches rely on 3D hash grids, which are difficult to scale to 4D.
    - Design a representation that efficiently incorporates time without excessive memory overhead.



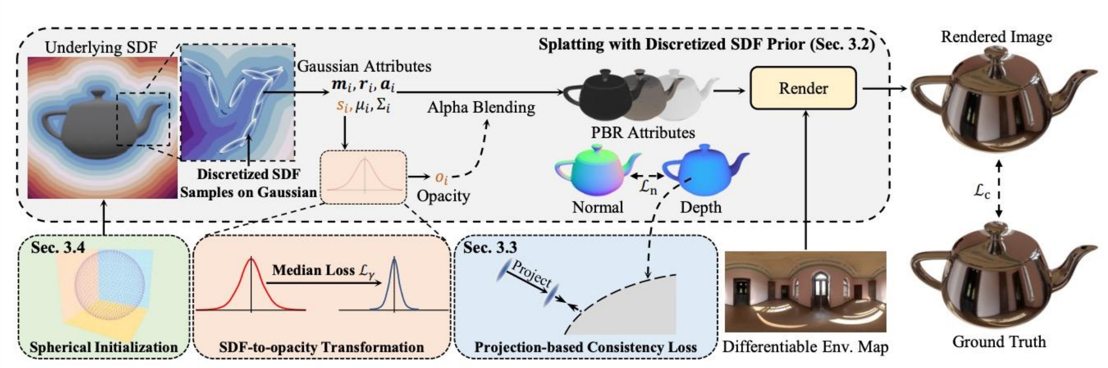


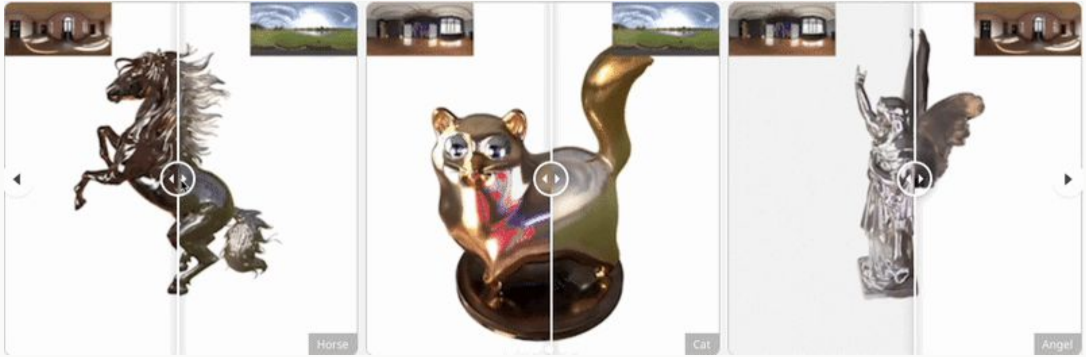


MoAngelo: Motion-Aware Neural Surface Reconstruction for Dynamic Scenes, Ebbed et. al 3DV 2026

B PG ✗
M Sem ✗
M Lab ✓

GML4: Inverse Rendering on 3D Gaussians

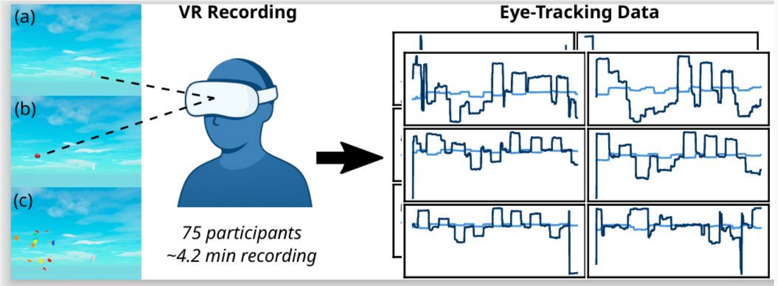


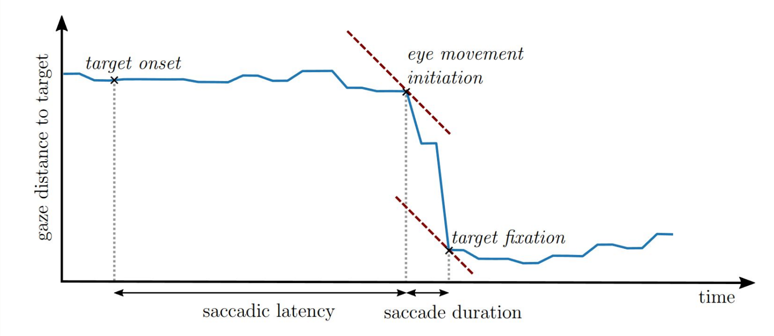


Gaussian Splatting with Discretized SDF for Relightable Assets, Zhu, et. al ICCV 2025
Relightable 3D Gaussians: Realistic Point Cloud Relighting with BRDF Decomposition and Ray Tracing, Cao, et. al ECCV 2024

B PG ✗
M Sem ✓
M Lab ✗

GML5: Support Diagnostics of Parkinson's Disease with VR-based Eyetracking





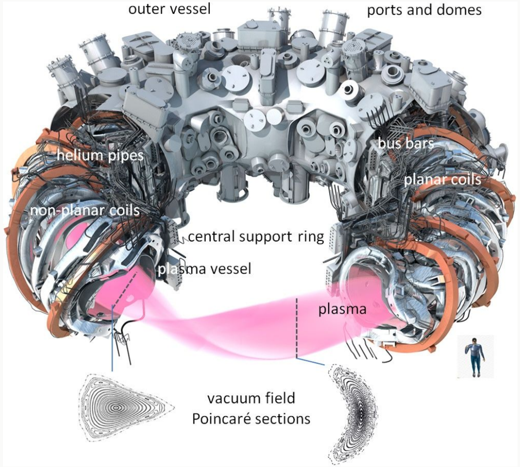
- Goal: Support diagnostic with eyetracking data from a simple VR game
- Distinguish between healthy controls, Parkinson's disease and other movement disorders
- Task: apply time series classification and finetune models

B PG ✓
M Sem ✗
M Lab ✓

More info: https://www.worldscientific.com/doi/epdf/10.1142/9789819824755_0016

GML6: Fusion Energy Generation

- Goal: safe and sustainable energy with fusion energy generation
- Requires plasma state (hot and high pressure)
- Current prototypes are not yet efficient enough
- Paper with dataset and background information: https://arxiv.org/pdf/2506.19583

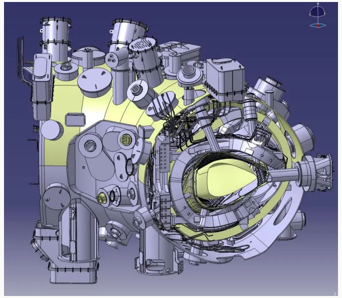


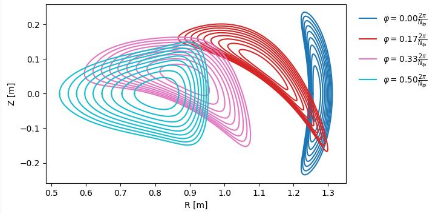
MPI for Plasma Physics

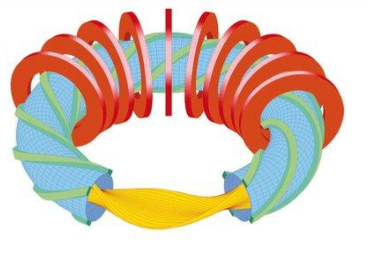
B PG ✓
M Sem ✗
M Lab ✓

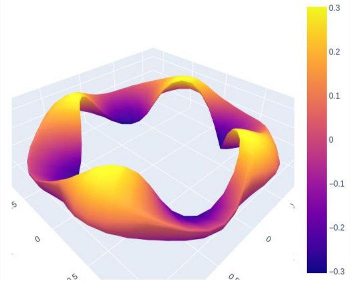
GML7: Stellarator - Plasma Shape Optimization

- 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, …)



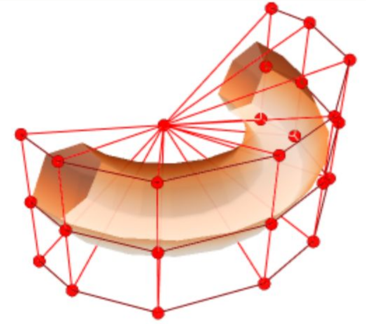




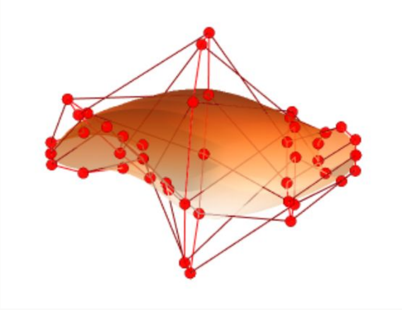


B PG ✓
M Sem ✗
M Lab ✓

GML8: Task: Improve B-Spline Surface Representation for Plasma Shapes



$$S(x) = \sum_{j=0}^{n-1} c_j B_{j,k;t}(x)$$



- Improve conversion between angle-based Fourier Representation and B-Spline Surfaces
- Apply local deformations and analyse impact on physics metrics

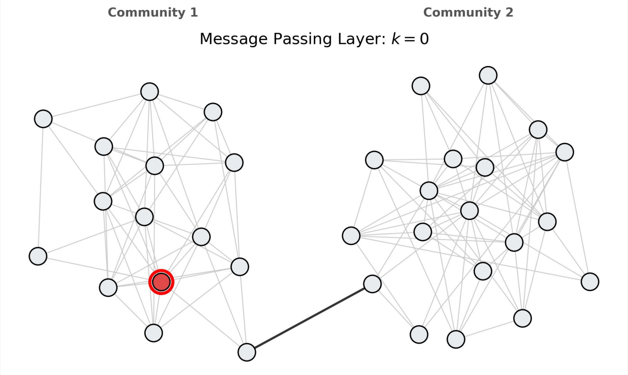
This project is affected by embargo restrictions.

B PG	✓
M Sem	✗
M Lab	✓

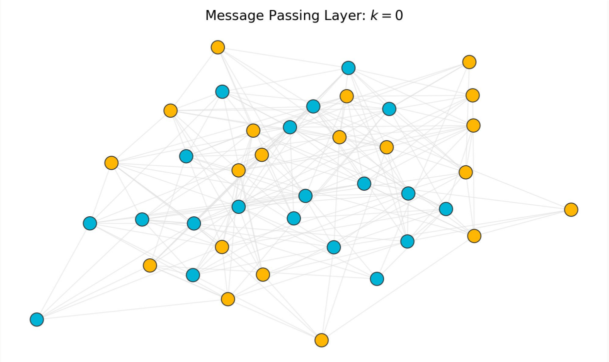
GML9. Diffeomorphic Spectral Rewiring for Graph Neural Networks (BPG/Lab/Seminar)

- **Graphs:** Mathematical way to represent complex interactions (e.g. Molecules, Social Networks, Road Traffic)
- **Graph Neural Networks:** Learning by asking, "Who are your neighbors?" Nodes update their state by aggregating data from 1-hop connections.
- **Why We Care:** Build deep GNNs to discover life-saving drugs faster or fluid dynamics simulations.

Oversquashing:



Oversmoothing:



GML9. Diffeomorphic Spectral Rewiring for Graph Neural Networks (BPG/Lab/Seminar)

- Rewire the graph to remove bottlenecks
- **How?** *Learn* to rewire by smoothly (diffeomorphic) warping the graph's spectrum

References:

- Diffusion Improves Graph Learning
- Understanding over-squashing and bottlenecks on graphs via curvature

B PG ✓
M Sem ✓
M Lab ✓

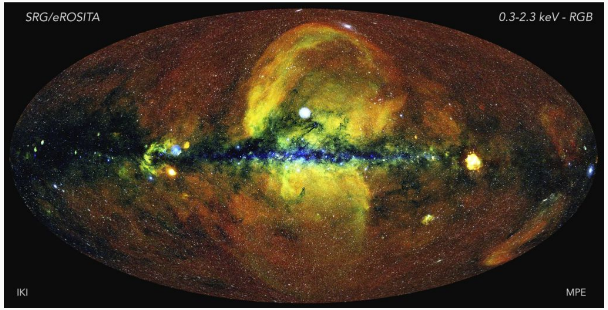
Advertisement for non-project-based lab/seminars

Join introduction meetings or check out eCampus for more information!

MA-INF 4244 Lab Deep Learning for the Physical Sciences

Introduction meeting: April 15th (tomorrow), 10:15 in room 3.035b

This semesters topic: astrophysics



B PG ✗
M Sem ✗
M Lab ✓

MA-INF 2228 Seminar Vision and Graphics (Role-Based)

B PG ✗
M Sem ✓
M Lab ✗

Introduction meeting: April 15th (tomorrow), 12:15 in room 3.035b

Concept: discussion-based seminar where each week you approach a paper from the perspective of a different role

- Paper Author
- Archaeologist
- Industry Practitioner
- Scientific Peer Reviewer
- Scientific Researcher
- Private Investigator

Thank you for you attention!

Any questions?