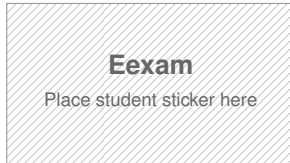




## Final ml3d endterm

Machine Learning for 3D Geometry (Technische Universität München)



**Note:**

- During the attendance check a sticker containing a unique code will be put on this exam.
- This code contains a unique number that associates this exam with your registration number.
- This number is printed both next to the code and to the signature field in the attendance check list.

## Machine Learning for 3D Geometry

**Exam:** IN2392 / Endterm

**Date:** Tuesday 9<sup>th</sup> August, 2022

**Examiner:** Prof. Dr. Angela Dai

**Time:** 13:00 – 14:30

	P 1	P 2	P 3	P 4	P 5	P 6	P 7
I							

### Working instructions

- This exam consists of **16 pages** with a total of **7 problems**.  
Please make sure now that you received a complete copy of the exam.
- The total amount of achievable credits in this exam is 110 credits.
- Detaching pages from the exam is prohibited.
- Allowed resources:
  - one **non-programmable pocket calculator**
  - one **analog dictionary** English ↔ native language
- Subproblems marked by \* can be solved without results of previous subproblems.
- **Answers are only accepted if the solution approach is documented.** Give a reason for each answer unless explicitly stated otherwise in the respective subproblem.
- Do not write with red or green colors nor use pencils.
- Physically turn off all electronic devices, put them into your bag and close the bag.

Left room from \_\_\_\_\_ to \_\_\_\_\_ / Early submission at \_\_\_\_\_

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# Department of Informatics, Technical University of Munich

## Exam on Machine Learning for 3D Geometry

Prof. Dr. Angela Dai

August 9, 2022 Summer 2022 90 Minutes

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### General Information:

- You have **90 Minutes** to solve the exam, which contains a total of 31 questions. You can achieve a maximum of 110 points.
- No additional resources are allowed.
- Do not write with red or green colors nor use pencils.
- **You need to submit this exam sheet with questions.**

### Multiple Choice Questions:

For the multiple choice questions, any number of answers can be correct:  
You get points individually per box,

- for a correct answer that is checked, and
- for a wrong answer that is not checked.

There are no negative points.

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## Part I: Multiple Choice

1. (2 points) Check all that apply: For a triangle mesh that is a manifold, which of the following is true?

- ☐ The intersection of any two triangles must be empty.
- ☐ Every edge must have at most two adjacent triangles.
- ☐ The intersection of any two triangles must have a common edge.
- ☐ All edges must have only a single adjacent triangle.

<input type="checkbox"/>	0
<input type="checkbox"/>	1
<input type="checkbox"/>	2

2. (2 points) Check all that apply: Which of the following is true for 3d representations?

- ☐ Point clouds can be converted to an implicit representation using Poisson Surface Reconstruction.
- ☐ Point clouds are more memory-efficient than dense grids.
- ☐ Given two implicit surfaces A and B, their union is always defined as  $\max(A, B)$ .
- ☐ One major advantage of dense grids is that neighbor operations are efficient.

<input type="checkbox"/>	0
<input type="checkbox"/>	1
<input type="checkbox"/>	2

3. (2 points) Check all that apply: Which of the following is true for multi-view learning :

- ☐ Can be combined with implicit surface neural networks.
- ☐ Cannot be combined with Point Cloud networks.
- ☐ Allows transfer learning from 2D datasets.
- ☐ Other 3D inputs are unnecessary when using them.

<input type="checkbox"/>	0
<input type="checkbox"/>	1
<input type="checkbox"/>	2

4. (2 points) Check all that apply: In a triangle mesh,

- ☐ Vertices cannot appear in more than one polygon.
- ☐ Every edge belongs to at least one polygon.
- ☐ All vertices must have the same degree.
- ☐ All polygons are closed and simple.

<input type="checkbox"/>	0
<input type="checkbox"/>	1
<input type="checkbox"/>	2

5. (2 points) Check all that apply: When estimating the transform between two rigid shapes,

- ☐ The transform contains rotation and translation for a total of 9 degrees of freedom.
- ☐ One usually aims for fewer correspondences than degrees of freedom.
- ☐ The geometry of both shapes may not be identical.
- ☐ Optimization must be iterative.

<input type="checkbox"/>	0
<input type="checkbox"/>	1
<input type="checkbox"/>	2

0 ☐  
1 ☐  
2 ☐

6. (2 points) Check all that apply: The following are appropriate distance measures for oriented point clouds

- ☐ Chamfer distance.
- ☐  $\ell_1$  distance.
- ☐ Earth Mover's (Wasserstein) Distance.
- ☐ Cosine distance of nearest neighbor points' normals.

0 ☐  
1 ☐  
2 ☐

7. (2 points) Check all that apply: The following deep network approaches can be used to learn semantic segmentation directly on a 3D volumetric grid:

- ☐ PointNet.
- ☐ 3D sparse convolutions.
- ☐ Geodesic convolutions.
- ☐ Standard 3D convolutions.

0 ☐  
1 ☐  
2 ☐

8. (2 points) Check all that apply: DeepSDF, which learns an implicit reconstruction of 3D shapes,

- ☐ Takes only a 3D  $(x, y, z)$  point location as input.
- ☐ Is trained encoder-decoder style.
- ☐ Is a convolutional architecture.
- ☐ Requires test time optimization to generalize.

0 ☐  
1 ☐  
2 ☐

9. (2 points) Check all that apply: Learning deformations of a template mesh:

- ☐ Can be used on CAD models for real scene observations.
- ☐ Cannot be done without changing mesh topology.
- ☐ Can allow for representation of arbitrary topologies.
- ☐ Cannot result in self-intersections.

0 ☐  
1 ☐  
2 ☐

10. (2 points) Check all that apply: Point cloud networks

- ☐ Are more memory-efficient for training than dense 3D convolutions.
- ☐ Cannot utilize neighbor information.
- ☐ Must consider input permutations.
- ☐ Are sparse convolutional networks.

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## Part II: 3D Surface Representations

1. (2 points) Explain the main steps in converting a triangle mesh into a point cloud using uniform sampling.

☐ 0  
☐ 1  
☐ 2

2. (2 points) Compare and contrast the use of dense volumetric convolutions with sparse volumetric convolutions. Name one advantage and one disadvantage for each.

☐ 0  
☐ 1  
☐ 2

3. (1 point) Explain the main steps in a multi-view shape recognition network that takes RGB images as inputs.

☐ 0  
☐ 1

- 
4. (1 point) Name one reason to use a signed distance field representation over an occupancy grid representation to characterize a surface.

0 ☐

1 ☐

5. (2 points) For two implicit surfaces  $f$  and  $g$  defined with positive values inside the surface and negative values outside the surface, explain how to compute the boolean intersection  $f \cap g$  and the boolean subtraction  $f - g$ .

0 ☐

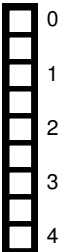
1 ☐

2 ☐

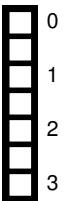
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## Part III: Geometric Registration

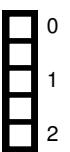
1. (4 points) Given perfect correspondences  $\{x_i\}, \{y_i\} \in \mathbb{R}^3$ , state the optimization objective (as a formula) and describe a non-iterative approach to estimate rotation  $\mathbf{R}$  and translation  $\mathbf{t}$ .



2. (3 points) Given two depth images A and B of an object, describe how to perform ICP between A and B. Why do we need an iterative solution instead of the solution to the previous III(1)? What are the requirements for ICP to succeed?



3. (2 points) When performing global shape registration with unknown correspondences, the brute-force solution of trying all possible different correspondence pairs is intractable. Name and briefly explain two solutions to make this problem tractable.

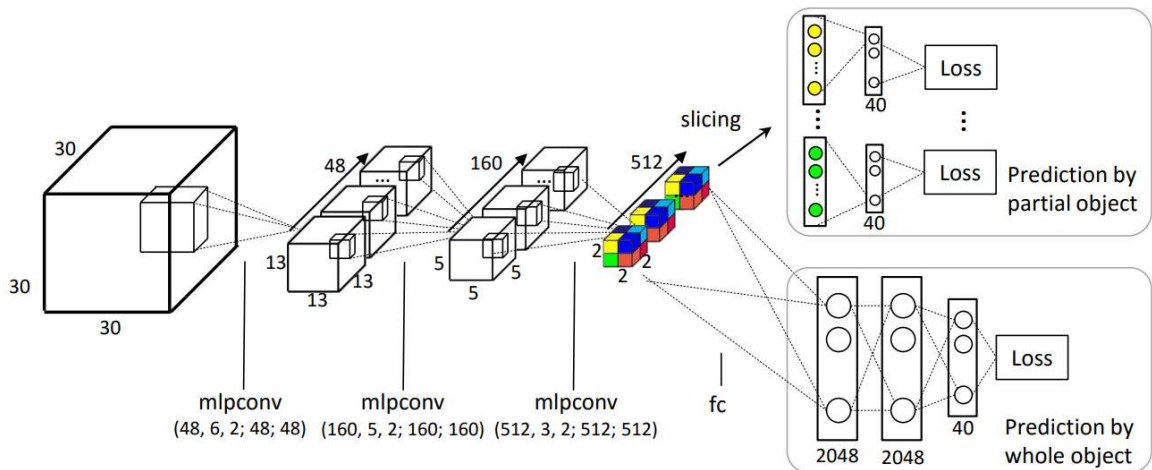




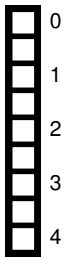
## Part IV: 3D Object Classification

1. (2 points) A variant of the 3DCNN architecture [Qi et al. '16] is shown in the diagram below. What representation space does the architecture use as input? Name and briefly explain one difference between the depicted 3DCNN architecture compared to a vanilla 3D CNN architecture (i.e., a stack of PyTorch Conv3D layers and ReLUs).

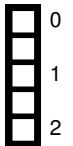
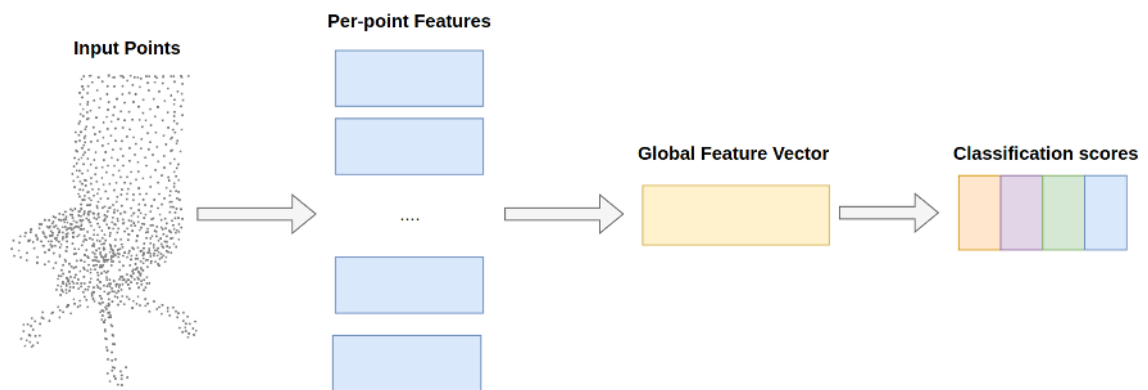
0  
1  
2



2. (4 points) Name two architectures that are invariant to input point cloud permutations. For each architecture named, explain how they achieve this invariance.



3. (2 points) Imagine you have a permutation-invariant point cloud classification network trained on ShapeNet, and you want to fine-tune that network for learning global shape embeddings for, e.g., shape retrieval from a database. Which layer output do you take, and why not the other layers?



## Part V: Shape and Scene Semantic Understanding

1. (1 point) Describe the key difference between outputs of 3D semantic segmentation and 3D instance segmentation on a point cloud.

0 ☐

1 ☐

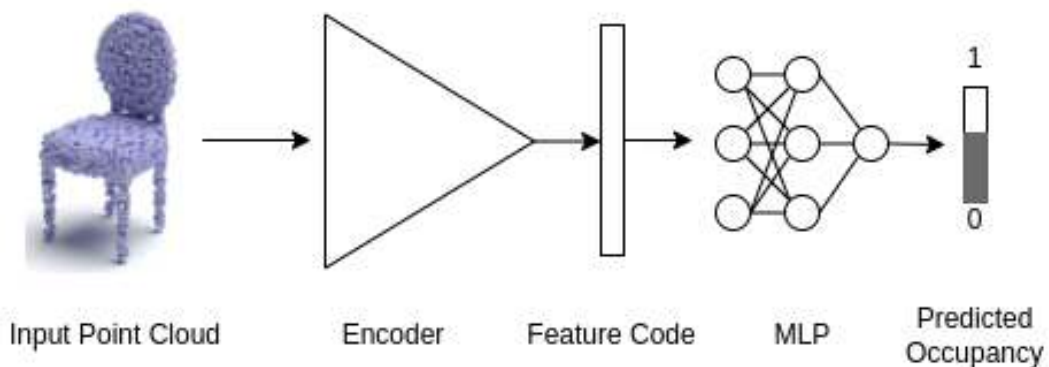
2. (2 points) The following figure shows a surface reconstruction network inspired by Occupancy Networks.

0 ☐

1 ☐

2 ☐

- How would you modify its architecture such that it can be used for part segmentation of objects?
- How would you modify its architecture such that it can be used for 3D shape reconstruction from a single image as input?



- 
3. (1 point) One challenge associated with moving from shape completion of objects to shape completion of scenes is the issue of the arbitrary scale of scenes (e.g., an object vs a building). Describe one approach to handle this scale variety in the shape completion of scenes.



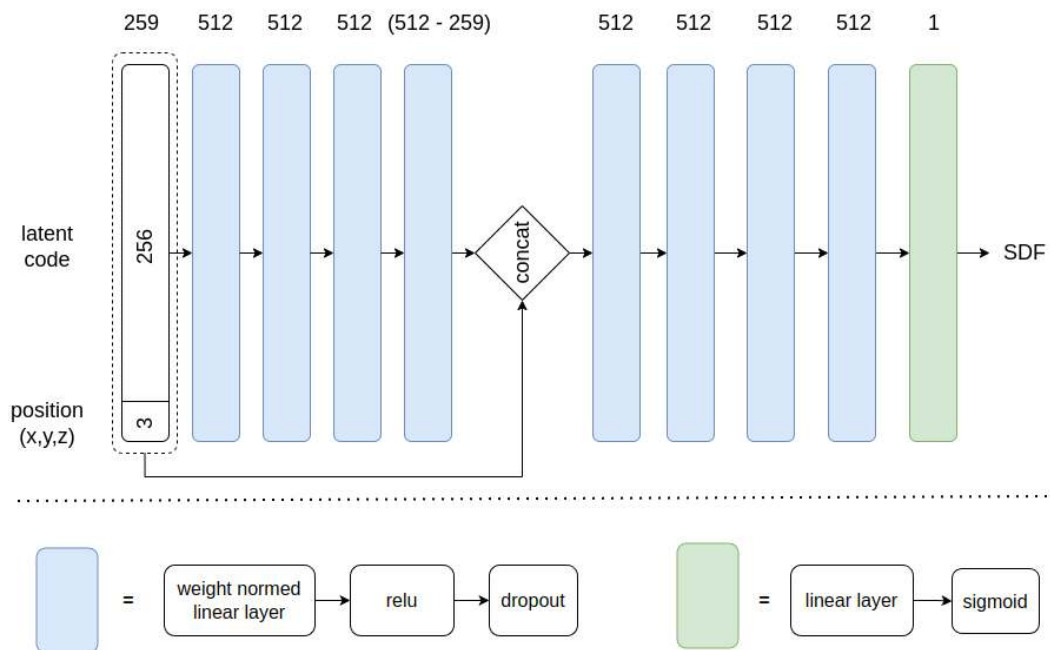
4. (1 point) Briefly describe the main conclusion that “3DMV: Joint 3D-Multi-View Prediction for 3D Semantic Scene Segmentation” provides for the relation of color and geometry for 3D scene segmentation.



## Part VI: Generative Models for 3D Reconstruction

- (3 points) In the lecture, you were introduced to Local Implicit Grids and Convolutional Occupancy Networks, two methods for scaling neural implicit functions to scene reconstruction. Briefly explain how each method achieves scaling neural implicit functions to scenes and what are their differences.

- (2 points) Your colleague came up with an implicit model for shape representation inspired from DeepSDF, but their model, shown below, cannot even overfit to one shape. Point out a fundamental issue with the model and explain why it is a problem.



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3. (2 points) Name two challenges in texture optimization for RGB-D scans.



4. (3 points) Supervised scene completion methods are typically trained with synthetic data since real-world scanned data is incomplete due to physical limitations in the scanning process, and thus cannot be used for supervision. Therefore, some recent works leverage self-supervision. Explain how to use self-supervision for 1) geometry and 2) color. Name one example that either uses geometry or color for self-supervision.



## Part VII: Project Questions

Please keep your answers short (do not exceed the given space below the questions!). Also, try not to spend more than 10 minutes on this part! We would advise you to work on this part in the last 10 minutes of the exam.

The actual grade you get from the project will be correlated with your project work, but we still require you to briefly answer the below questions.

1. (25 points) Describe your project task; i.e., what is your problem statement and how did you plan to approach it? For instance describe the theoretical foundation behind the approach (i.e., what you promised in your proposal).

2. (25 points) Give a high-level overview of the technical solution to your problem.

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## Additional Space

Please clearly indicate which questions are answered on this page.



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## **Additional Space**

Please clearly indicate which questions are answered on this page.