Assignment ml3d endterm

Machine Learning for 3D Geometry (Technische Universität München)

Chair of Computer Graphics and Visualization
School of Computation, Information and Technology
Technical University of Munich

E0039
Place student sticker here

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 21st February, 2023
Examiner:	Prof. Dr. Angela Dai	**Time:**	11:00 – 12:30

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

Working instructions

- This exam consists of **12 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 100 credits.
- Detaching pages from the exam is prohibited.
- Allowed resources: none
- 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 __________

☐ Exam empty

Problem 1 Multiple Choice (20 credits)

Mark correct answers with a cross ☒
To undo a cross, completely fill out the answer option ■
To re-mark an option, use a human-readable marking ×■

For each subproblem,

- Any number of answers can be correct, including all and zero (!)
- You get full credits if all boxes are correct, and 0 otherwise

a) For a triangle mesh that is a manifold, which of the following is true?

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

b) Which of the following is true for 3D representations?

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

c) Multi-view learning can be used in combination with:

- ☐ Mesh neural networks.
- ☐ Implicit surface neural networks.
- ☐ Dense volumetric neural networks.
- ☐ Point cloud neural networks.

d) In a polygon mesh,

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

e) When estimating the transform between two rigid shapes,

- ☐ The geometry of both shapes does not have to be identical.
- ☐ One must aim for exactly the same number of correspondences as degrees of freedom.
- ☐ The transform contains rotation and translation for a total of 4 degrees of freedom.
- ☐ A shape descriptor is always used to establish point correspondences.

f) An ideal distance measure for shape alignment ...

- [ ] Must be symmetric and follow the triangle inequality.
- [ ] Is often measured by aggregating correspondences between the shapes.
- [ ] Is an ℓ_2 distance.
- [ ] Supports partial matches.

g) The following deep network approaches cannot directly operate on 3D meshes:

- [ ] PointNet.
- [ ] Geodesic convolutions.
- [ ] Message-passing along mesh edges and/or faces.
- [ ] 3D sparse convolutions.

h) Parametric surfaces ...

- [ ] Require fewer points to represent a surface than a triangle mesh.
- [ ] Are hard to manipulate after the initial generation.
- [ ] Require more steps for rendering than triangle meshes.
- [ ] Implicitly encode a shape's inside and outside.

i) Learning deformations of a template mesh ...

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

j) Sparse 3D convolutional networks (CNNs) ...

- [ ] Are more memory-efficient for training than dense 3D CNNs for the same voxel resolution.
- [ ] Can operate directly on raw point cloud data.
- [ ] Store fewer weights per convolution than dense 3D convolutions for the same kernel size.
- [ ] Learns the exact same features as dense convolutions.

Problem 2 3D Surface Representations (8 credits)

0 1 2

a) You have a network that predicts a complete shape in the form of a dense SDF grid. Name a method to generate a triangle mesh from this representation (not learning-based), and explain its main steps.

0 1 2

b) You want to compare your generated triangle mesh to a ground-truth shape represented as a point cloud. Explain the main steps in converting your mesh into a point cloud.
Note: The points should be uniformly distributed on the mesh surface.

0 1

c) Why can dense volumetric 3D surface representations be computationally inefficient and what is a possible alternative, if you still want to use 3D CNNs?

0 1

d) Name one reason to use a signed distance field representation over an occupancy grid representation to characterize a surface.

0 1 2

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

Problem 3 Geometric Registration (9 credits)

a) You are given two far-apart rigid shapes A and B with unknown rotation and translation and without any correspondences between them. Explain a two-step process used to establish global shape correspondences between them and two possible existing approaches for the first step.

0 1 2

b) After establishing correspondences $\{x_i\}, \{y_i\} \in \mathbb{R}^3$, you now want to register the two shapes. State the optimization objective (as a formula) and describe a non-iterative least-squares optimization approach to estimate rotation $\mathbf{R}$ and translation $\mathbf{t}$.

0 1 2 3 4

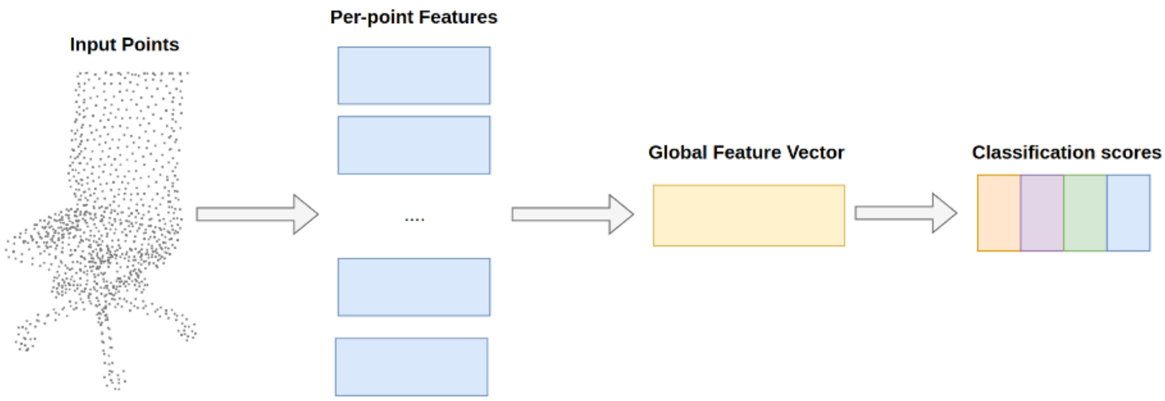
c) After the steps in questions (a) and (b), your registration still shows a small error so you decide to apply an additional method for refinement. This approach could not have been applied in the first step. Name and briefly explain this approach, and describe why could we not have applied it in the first step.

0 1 2 3

Problem 4 3D Object Classification (8 credits)

0 1 2 3 4

a) The picture below shows a very high-level overview of the PointNet approach for shape classification presented in the lecture.
Explain what happens for each arrow (i.e. how does it compute per-point features, the global feature vector, and the classification scores).
What is the main problem that the global feature aggregation has to solve and how does it do so?



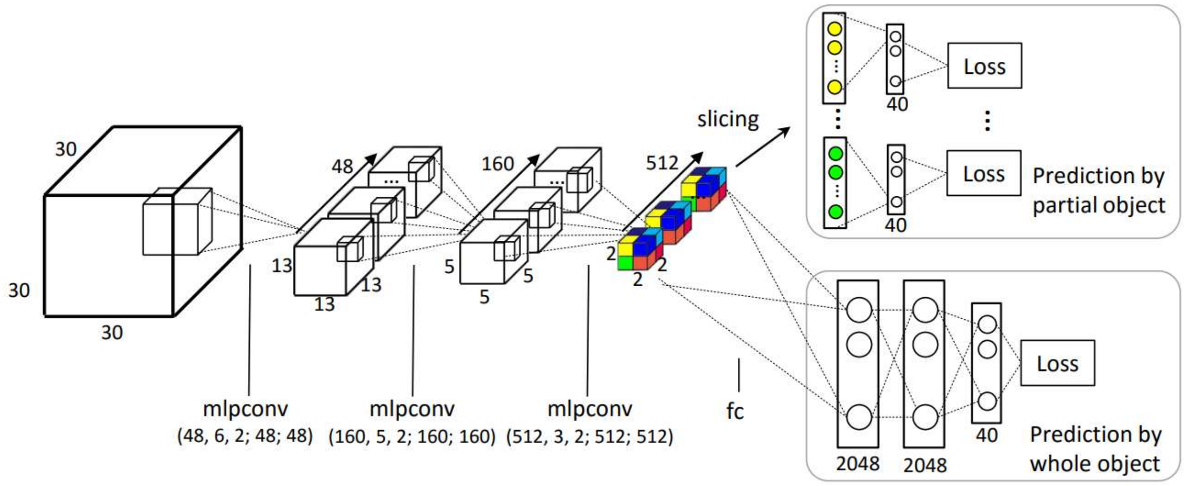
0 1 2

b) You want to use PointNet for shape segmentation instead of classification. What is the main difference to shape classification in terms of the architecture, and which layer outputs do you need to use?

Page empty

c) 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



cit-ml3d-2-20230221-E0039-07

cit-ml3d-2-20230221-E0039-07

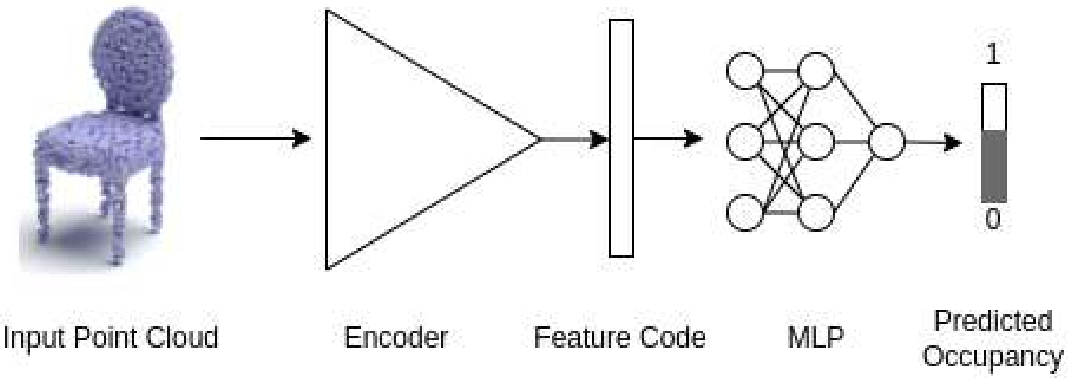
Problem 5 Shape and Scene Semantic Understanding (5 credits)

0
1

a) You are provided with 1000 shapes from the ShapeNet dataset, all belonging to the same class. The shapes come only as geometry, i.e. without any texture or semantic information. Your task is to perform part segmentation for each of these shapes. Name a method you can use in this scenario for this task.

0
1
2

b) The following figure shows a surface reconstruction network inspired by Occupancy Networks. How would you modify its architecture such that ...
(1) it can be used for part segmentation of objects?
(2) it can be used for 3D shape reconstruction from multi-view images as input?



0
1

c) Name and explain one existing method for 3D shape detection in point clouds.

0
1

d) Describe the conclusion that RevealNet provides for the relation between completion and segmentation for instance segmentation.

cit-ml3d-2-20230221-E0039-08
cit-ml3d-2-20230221-E0039-08
cit-ml3d-2-20230221-E0039-08

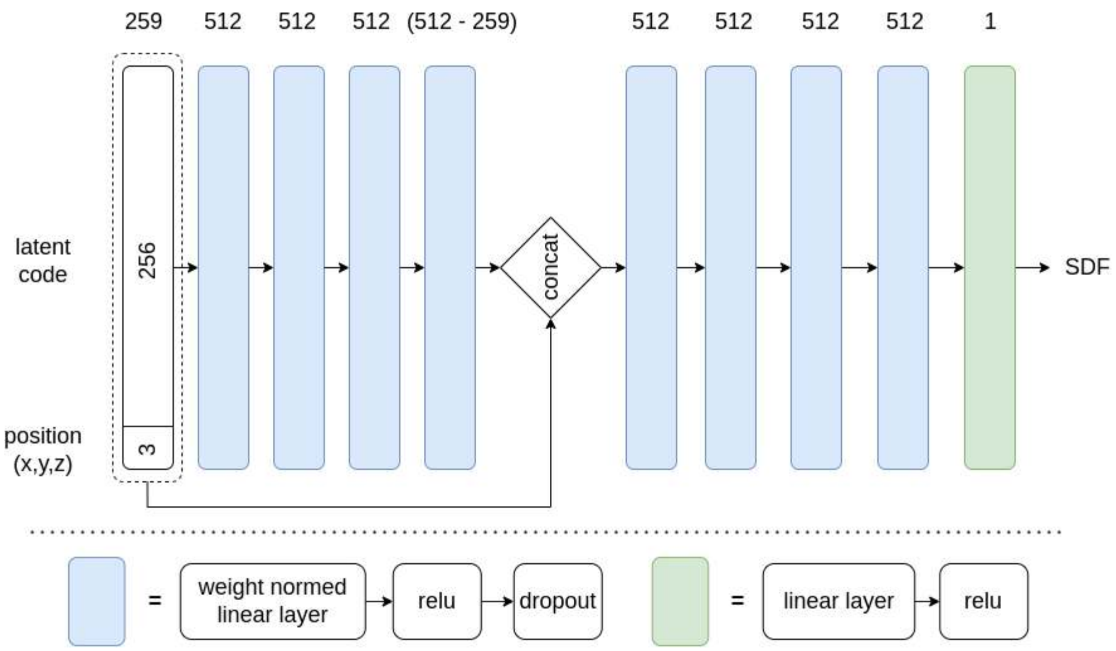
Problem 6 Generative Models for 3D Reconstruction (10 credits)

a) In the lecture, you were introduced to DeepSDF, which is an auto-decoder. How is DeepSDF trained without an encoder? During test time, how can DeepSDF reconstruct partially observed shapes without an encoder?

0 1 2

b) Your colleague came up with an implicit model for shape representation inspired by DeepSDF, but their model, shown below, cannot even overfit one shape. Point out and explain the fundamental issue with the model and suggest one way to fix it.

0 1 2



cit-ml3d-2-20230221-E0039-09

0
1
2
3

c) After experiments on single object shapes, you now want to reconstruct entire scenes. You tried both DeepSDF and Occupancy Networks but they do not generate good results. Name and briefly explain one implicit reconstruction method that is capable of reconstructing whole scenes. Point out the component that makes this method work better on scenes than DeepSDF or Occupancy Networks.

0
1
2

d) 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. Name one such method and how it uses self-supervision for geometry.

0
1

e) Another challenge for 3D reconstruction of scenes is handling varying scales (e.g., a small bathroom vs. a large living room), without knowledge of a maximum extent. Describe one approach to handle this issue effectively.

Problem 7 **Project Questions (40 credits)**

This part of the exam represents the project you were working on during the semester. The number of credits here is determined by your project grade.
The first box will be filled by us, and your task is to answer the two project-related questions in both boxes below. We will take your answers into account for your individual project grade.
Please keep your answers short (do not exceed the given space below the questions!).
We would advise you not to spend too much time on this section and to work on this part in the last 15 minutes of the exam.

Project Score: We will fill in your project score here during correction; please leave this box blank.

`Presentation: __/10, Method: __/10, Questions: __/5, Report: __/15`

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).

Give a high-level overview of the technical solution to your problem.

Additional space for solutions–clearly mark the (sub)problem your answers are related to and strike out invalid solutions.