Department of Informatics, Technical University of Munich Exam on Machine Learning for 3D Geometry

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February 9, 2022 Winter 2021 90 Minutes

General Information:

- You have **90 Minutes** to solve the exam, which contains a total of 31 questions. You can achieve a maximum of 100 points.
- No additional resources are allowed.
- Do not write with red or green colors nor use pencils.
- Only submit your personalized blackened exam sheet that you downloaded from TUMExam.
 DO NOT 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.

Part I: Multiple Choice

1.	(2 points) ing is true	Check all that apply: For a triangle mesh which is a manifold, which of the follow-?
		The intersection of any two triangles must be non-empty.
		Every edge must have at most two adjacent triangles.
		The intersection of any two triangles must have a common edge.
		Some edges may have only a single adjacent triangle.
	Mark your	solution on the blackened exam sheet.
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 Marching Cubes.
		Point clouds represent surfaces more efficiently than dense grids.
		Given two implicit surfaces A and B, their intersection is always defined as min(A, B).
		One major disadvantage of dense grids is that neighbor operations are expensive.
	Mark your	solution on the blackened exam sheet.
3.	(2 points)	Check all that apply: Multi-view learning can be used in combination with:
		Dense volumetric neural networks.
		Point cloud neural networks.
		Mesh neural networks.
		Implicit surface neural networks.
	Mark your	solution on the blackened exam sheet.
4.	(2 points)	Check all that apply: In a polygon mesh,
		Edges may intersect each other.
		Every edge belongs to at least one polygon.
		All vertices must have the same degree.
		All polygons are closed and simple.
	Mark your	solution on the blackened exam sheet.
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 4 degrees of freedom.
		One usually aims for more correspondences than degrees of freedom.
		The geometry of both shapes must be identical.
		A shape descriptor is always used to establish point correspondences.
	Mark your	solution on the blackened exam sheet.

6.	(2 points) Check all that apply: A good distance measure for shape alignment
	\Box Is often measured by aggregating correspondences between the shapes.
	\square Is an ℓ_2 distance.
	☐ Must be symmetric and follow the triangle inequality.
	☐ Supports partial matches.
	Mark your solution on the blackened exam sheet.
7.	(2 points) Check all that apply: The following deep network approaches can be used to learn semantic segmentation directly on a 3D mesh:
	☐ 3D sparse convolutions.
	☐ Geodesic convolutions.
	☐ Message-passing along mesh edges and/or faces.
	☐ Convolutions on mesh edges as a basis.
	Mark your solution on the blackened exam sheet.
8.	(2 points) Check all that apply: DeepSDF, which learns an implicit reconstruction of 3D shapes,
	$\ \square$ Takes only a 3D (x, y, z) point location as input.
	☐ Directly outputs a 3D mesh reconstruction of a shape.
	\square Requires only a single forward pass through the network to generate a shape.
	\square Is not bound to any explicit surface resolution.
	Mark your solution on the blackened exam sheet.
9.	(2 points) Check all that apply: Learning deformations of a template mesh:
	☐ Can be used on CAD models to real scene observations.
	\Box Can be done by predicting vertex offsets.
	☐ Can allow for representation of arbitrary topologies.
	☐ Cannot result in self-intersections.
	Mark your solution on the blackened exam sheet.
10.	(2 points) Check all that apply: sparse 3D convolutions
	☐ Are more memory-efficient for training than dense 3D convolutions for the same voxel resolution.
	☐ Store fewer weights per convolution than dense 3D convolutions for the same kernel size.
	☐ Can operate directly on raw point cloud data.
	☐ Cannot be used for generative or reconstruction tasks.
	Mark your solution on the blackened exam sheet.

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Part II: 3D Surface Representations

1. (2 points) Explain the main steps in converting an oriented point cloud into a surface mesh representation without the use of a deep network.

Write your solution on the blackened exam sheet.

2. (2 points) Compare and contrast the use of dense volumetric data with point cloud input for a deep network. Name one advantage and one disadvantage for each data modality.

Write your solution on the blackened exam sheet.

3. (1 point) Name one advantage of incorporating multi-view information into a neural network which previously operated only on surface geometry information.

Write your solution on the blackened exam sheet.

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

Write your solution on the blackened exam sheet.

5. (2 points) 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 $f \cup g$ and the boolean subtraction f - g.

Part III: Geometric Registration

1. (5 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} .

Write your solution on the blackened exam sheet.

2. (2 points) You are given two rigid shapes A and B without any correspondences between them. Describe a method (non deep learning based) that can be used to find the rigid transformation between them.

Write your solution on the blackened exam sheet.

3. (2 points) Name and explain (in one sentence each) two possible approaches that can be taken for a global registration of shapes in arbitrary positions.

Part IV: 3D Object Classification

1. (4 points) PointNet is a popular network architecture that takes in shapes as point clouds and predicts their class while being agnostic to the input point ordering. How does it achieve this?

Write your solution on the blackened exam sheet.

2. (2 points) Imagine you have version of PointNet, pretrained for classification on the ShapeNet database. You now want to use this to compute a global shape descriptor for previously unseen shapes during test time. How would you modify the network architecture and after which layer do you extract the global descriptor features?

Write your solution on the blackened exam sheet.

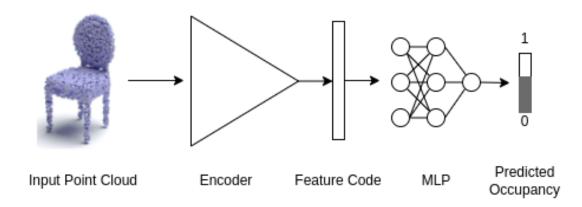
3. (2 points) Name one follow-up work that improves classification performance by also capturing local structures of shapes. How does it do so and what are the essential operations newly introduced in this architecture?

Part V: Shape and Scene Segmentation

1. (1 point) You are provided with 5000 shapes from the ShapeNet dataset, all belonging to the chair 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.

Write your solution on the blackened exam sheet.

2. (2 points) The following figure shows a surface reconstruction method inspired from Occupancy Networks. How would you modify its architecture and training supervision such that it can be used for part segmentation of objects?



Write your solution on the blackened exam sheet.

3. (1 point) One challenge associated with moving from part segmentation of objects to semantic segmentation of scenes is the issue of the arbitrary scale of scenes (e.g., a room vs a building). Describe one approach to handle this scale variety in semantic segmentation of scenes.

Write your solution on the blackened exam sheet.

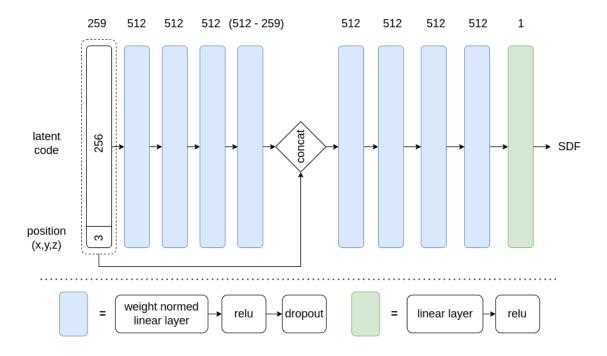
4. (1 point) Describe the conclusion that RevealNet provides for the relation between completion and segmentation for instance segmentation.

Part VI: Generative Models for 3D Reconstruction

1. (2 points) In the lecture, you were introduced to DeepSDF and Occupancy Networks, two very similar methods for shape reconstruction and representation. Describe two differences between these methods.

Write your solution on the blackened exam sheet.

2. (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.



Write your solution on the blackened exam sheet.

3. (3 points) Explain the idea behind Convolutional Occupancy Networks. For what kinds of reconstruction problems do you expect Convolutional Occupancy Networks to significantly outperform methods like Occupancy Networks and DeepSDF?

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. Name and explain a method which overcomes this issue and learns scene completion from real world scans.

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 15 minutes on this part! We would advise you to work on this part in the last 15 minutes of the exam.

1. (20 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).

Write your solution on the blackened exam sheet.

2. (20 points) Give a high-level overview of the technical solution of your problem.