

# Nuages de Points et Modélisation 3D

7 - Machine learning IV

## Overview



Machine learning courses

- Surface reconstruction
- Descriptors and machine learning
- Image based processing
- Geometric deep learning
- Convolutional and Transformer based architectures
- Tasks and corresponding architectures

Today

## Course overserview



#### • Tasks

- Classification and segmentation
- Detection from point cloud
- Scene completion
- Generation
- Surface reconstruction
- Self-supervised learning
  - Point cloud only pretraining
  - Distillation
- Domain adaptation
- Open world

## Course overserview



#### • Tasks

- Classification and segmentation
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  - Distillation
- Domain adaptation
- Open world

Next week: QCM + (opening on multiview and rendering)





## Classification and semantic segmentation





## Detection

I - Tasks

# Put oriented boxes around objects of interest





### Detection

I - Tasks

Second





## Scene completion

I - Tasks

Input: lidar scan

**Output:** completed voxel scene with semantics





## Scene completion



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## Generation (e.g. diffusion models)





## Generation (e.g. diffusion models)





## Generation (e.g. diffusion models)

I - Tasks



Zhou et al. "3d shape generation and completion through point-voxel diffusion." ICCV. 2021.

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## Generation (e.g. diffusion models)





## Generation (e.g. diffusion models)



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## Generation (e.g. diffusion models)





## Surface reconstruction

I - Tasks



**Occupancy Networks: Learning 3D Reconstruction in Function Space** 

Mescheder, Lars and Oechsle, Michael and Niemeyer, Michael and Nowozin, Sebastian and Geiger, Andreas Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2019



## Surface reconstruction





## Surface reconstruction





## II - Self-supervised learning



## Supervised learning

Self-supervised learning



Train with annotated data

- Annotations are costly
- Limitation of the database size



## **Frugal learning**

Self-supervised learning

Objective: learning with less annotations



## Self-supervision

What? learn useful representations without annotations

Why? better performance when finetuning / data-efficiency



Step 2: finetuning (supervised)



#### ALSO: Automotive Lidar Self-Supervision by Occupancy Estimation



#### **Context reconstruction vs local reconstruction**



#### **Context reconstruction vs local reconstruction**



#### Local reconstruction [POCO head]

- everywhere, from features of neighboring points
- $\Rightarrow$  (too) detailed geometry

#### **Context reconstruction [ALSO head]**

- of a 1 meter ball, from each single feature point
⇒ rough geometry, more suited for object recognition

POCO: Point Convolution for Surface Reconstruction, A. Boulch, R. Marlet, CVPR 2022

#### **Context reconstruction vs local reconstruction**



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### Supervision





occupancy

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#### Supervision



#### **Supervision**



### Self-supervised occupancy - Query point generation





#### Along lidar lines of sight

**Empty queries:** from sensor to observed point

**Full queries:** just behind the point (max distance  $\delta$  = 0.1 m)

#### **Self-supervision**





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#### **Downstream tasks**



- remove occupancy head
- add a single linear layer
- finetune the whole network

#### Semantic segmentation - 1% annotated data



ALSO





## II - Self-supervision

Contrastive learning

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#### **Contrastive learning**



#### **Contrastive learning**





#### **Contrastive learning**





#### **Contrastive self-supervised learning for point clouds**

Contrastive methods



PointContrast

PointContrast

+++ Easy to implement

- - - Contrast in the same object

#### **Contrastive self-supervised learning for point clouds**

#### Contrastive methods



SegContrast / TARL

+++ Efficient thanks to object segmentation (temporal for TARL)

- - - Difficult to set up  $\rightarrow$  rely on HDBScan (hyperparameters)

#### **Contrastive self-supervised learning for point clouds**

#### Contrastive methods



#### **BEVContrast**

+++ Simple → easy projection in BEV +++ Object separation approximation with BEV cells

#### **BEVContrast**





#### **BEVContrast**

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Dataset	Method	0.1%		1%		10%		50%		100%	
	No pre-training	21.6	±0.5	35.0	±0.3	57.3	±0.4	69.0	±0.2	71.2	±0.2
	PointContrast <sup>†</sup> [40]	27.1	$\pm 0.5$	37.0	$\pm 0.5$	58.9	±0.2	69.4	$\pm 0.3$	71.1	±0.2
nuScenes	DepthContrast <sup>†</sup> [46]	21.7	±0.3	34.6	$\pm 0.5$	57.4	$\pm 0.5$	69.2	±0.3	71.2	$\pm 0.2$
	ALSO [3]	26.2	$\pm 0.5$	37.4	$\pm 0.3$	59.0	±0.4	69.8	$\pm 0.2$	71.8	$\pm 0.2$
	BEVContrast (ours)	26.6	$\pm 0.5$	37.9	±0.4	59.0	±0.6	70.5	$\pm 0.2$	72.2	±0.1
	No pre-training	30.0	±0.2	46.2	±0.6	57.6	±0.9	61.8	±0.4	62.7	±0.3
SemanticKITTI	PointContrast <sup>‡</sup> [40]	32.4	$\pm 0.5$	47.9	$\pm 0.5$	59.7	$\pm 0.5$	62.7	$\pm 0.3$	63.4	$\pm 0.4$
	SegContrast [29]	32.3	$\pm 0.3$	48.9	$\pm 0.3$	58.7	$\pm 0.5$	62.1	$\pm 0.4$	62.3	$\pm 0.4$
	DepthContrast <sup>†</sup> [46]	32.5	$\pm 0.4$	49.0	$\pm 0.4$	60.3	$\pm 0.5$	62.9	$\pm 0.5$	63.9	$\pm 0.4$
	STSSL [39]	32.0	$\pm 0.4$	49.4	$\pm 1.1$	60.0	$\pm 0.6$	62.9	$\pm 0.7$	63.3	$\pm 0.3$
	ALSO [3]	35.0	$\pm 0.1$	50.0	$\pm 0.4$	60.5	$\pm 0.1$	63.4	$\pm 0.5$	63.6	$\pm 0.5$
	TARL [30]	37.9	$\pm 0.4$	52.5	$\pm 0.5$	61.2	±0.3	63.4	$\pm 0.2$	63.7	±0.3
	BEVContrast (ours)	39.7	±0.9	53.8	±1.0	61.4	±0.4	63.4	$\pm 0.6$	64.1	±0.4



## II - Self-supervision

Distillation

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### Sensor setup



Example from nuScenes



#### Task of interest: point cloud semantic segmentation



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## SEAL - Segment any point cloud











2D features



2D features

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Credit Gilles Puy







## **III - Domain adaptation**

## Unsupervised domain adaptation



Target (no annotations) Domain gapDifferent sensorsDifferent locationsDifferent objects⇒ source model performs poorlyAdaptation

Use target data to enhance performances

⇒ prevent collapse



## Example - sensor gap

#### Domain adaptation



(a) captured by a 64-beam LiDAR (b) captured by a 32-beam LiDAR



## Complete and label

#### Domain adaptation



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## SALUDA

#### Domain adaptation





## SALUDA

#### Domain adaptation





## III - Open World

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## Open vocabulary

#### **Classic benchmarks**

- Closed vocabulary setup
- With definition of a **finite set** of classes
- Training of model in **fully-supervised** fashion
  - Requires a lot of annotation



#### Cityscapes dataset, 30 classes

[road, sidewalk, parking, rail track, person, rider, car, truck, bus, on rails, motorcycle, bicycle, caravan, trailer, building, wall, fence, guard rail, bridge, tunnel, pole, traffic sign, traffic light, vegetation, terrain, sky]



Pascal VOC dataset, 20 classes

[person, bird, cat, cow, dog, horse, sheep, aeroplane, bicycle, boat, bus, car, motorbike, train, bottle, chair, dining table, potted plant, sofa, tv/monitor]

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## Open vocabulary

#### The world is complex











CLIP





- Contrastive learning
  - Contrast positive/negative pairs
- Trained using 400 millions (image / text) pairs extracted from internet
  - o Meta-data
  - Legends



### OpenScene



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## OpenScene



Peng, Songyou, et al. "Openscene: 3d scene understanding with open vocabularies." CVPR. 2023.



### OpenScene



Input 3D Point Cloud



**Zero-shot Semantic Segmentation** 



"soft" - Property

1



"metal" - Material



"kitchen" - Room Type



"sit" - Affordance



"work" - Activity







Link to video

https://pengsongyou.github.io/openscene



## Conclusion and practical session

## Conclusion



A very short overview of some tasks

- There are many other
- Only few methods were presented, not state-of-the-art anymore

Practical session

Open Vocabulary on point cloud with MaskCLIP