

Generative Zero-Shot Learning for Semantic Segmentation of 3D Point Clouds

Poster presentation - 3DV 2021

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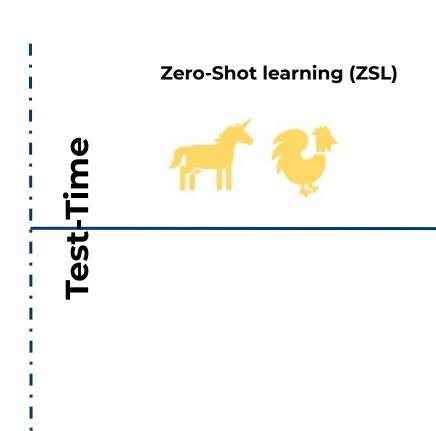


Zero-Shot learning

Training







VALEO RESERVED

Zero-Shot learning

Fraining





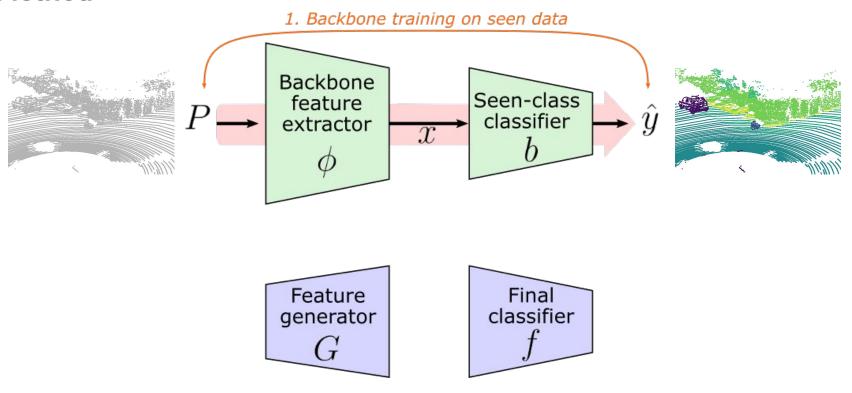
Zero-Shot learning (ZSL)

Generalized Zero-Shot learning (GZSL)

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VALEO RESERVED Valeo

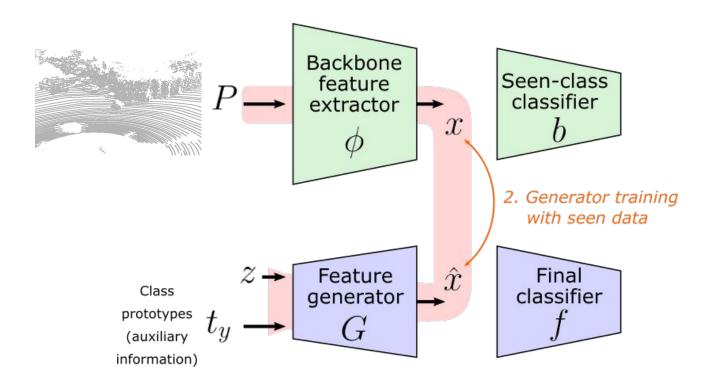
Method¹⁾



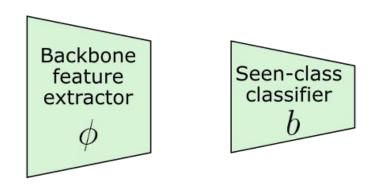
1) Adapted from:

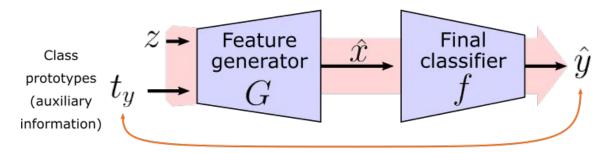
Bucher et al. Generating visual representations for zero-shot classification. ICCV, 2017. Bucher et al. Zero-shot semantic segmentation. NeurIPS, 2019.

Method



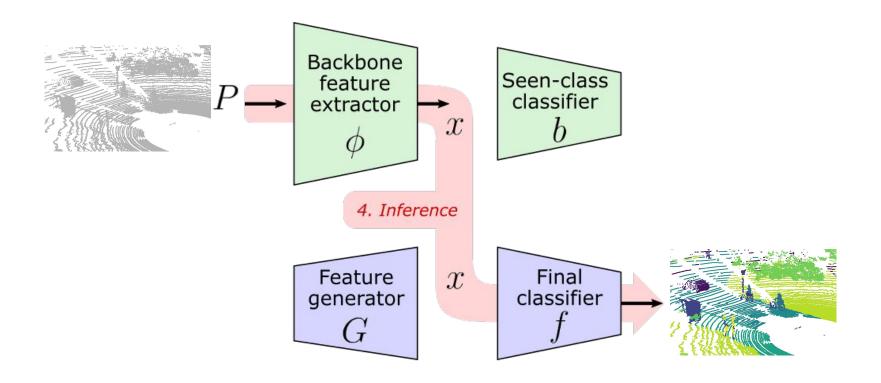
Method





3. Classifier training on generated unseen data (+ seen for GZSL)

Method



Experiments - Classification ZSL

		Full		ZSL	
Method	Gener- ative	super- vision Acc.	W2V Acc.	GloVe Acc.	Glove + W2V Acc.
PointNet	li s	89.2			
f-CLSWGAN ¹⁾ *	√		20.7	_	_
CADA-VAE ¹⁾ *	✓		23.0	-	-
$ZSLPC^{2)}$			28.0	20.9	20.5
MHPC3)			33.9	28.7	-
3DGenZ (ours)	✓		28.6	29.3	36.8

^{*:} adaptation of 2D methods to 3D point clouds, implemented in 1).

¹⁾ Cheraghian et al. Transductive zero-shot learning for 3D point cloud classification. WACV, 2020

²⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

³⁾ Cheraghian et al. Mitigating the hubness problem for zero-shot learning of 3d objects. 2019.

Bias problem in Generalized Zero-Shot learning (GZSL)

Confusion matrix for unseen classes (GZSL on Modelnet40)

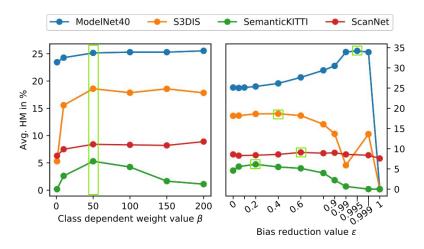


Semantic Segmentation is naturally in GZSL

Bias problem and reduction

Additional bias reduction techniques

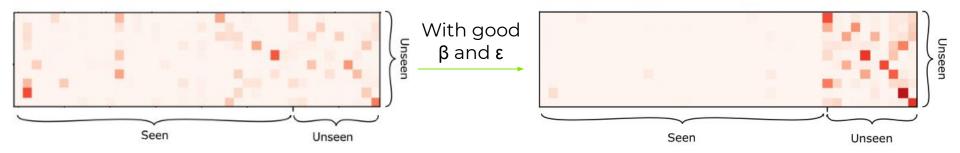
- Class-dependant weighting: Loss for unseen classes is weighted (factor $\beta > 1$) in classifier training
- **Calibrated Stacking**: Subtracting a small value ε from the seen-class score (after softmax) at test time
- β and ϵ are Hyperparameters



Bias problem and reduction

Additional bias reduction techniques

- Class-dependant weighting: Loss for unseen classes is weighted (factor $\beta > 1$) in classifier training
- Calibrated Stacking¹⁾: Subtracting a small value ϵ from the seen-class score (after softmax) at test time
- β and ϵ are Hyperparameters



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Experiments - Classification GZSL

	Full	Full GZSL										
Method		super-			W2V			GloVe	2	Glo'	Ve + V	W2V
	Gener- ative	vision Acc.	Bias reduct.	I	Acc.	НМ	Acc.	Acc.	НМ	\mathcal{S}	Acc.	НМ
PointNet		89.2										
f-CLSWGAN ¹⁾ *	√			76.3	3.7	7.0	-	-	-	-	-	-
CADA-VAE ¹⁾ *	✓			84.7	1.3	2.6	-	-	-	-	-	-
$ZSLPC^{2)}$				40.1	22.5	28.8	49.2	18.2	26.6	-	-	-
$MHPC^{3)}$			✓	53.8	26.2	35.2	53.8	25.7	34.8	-	-	-
3DGenZ (ours)	✓		✓	48.8	29.3	36.6	44.7	28.4	34.7	47.8	36.5	41.3

^{*:} adaptation of 2D methods to 3D point clouds, implemented in 1).

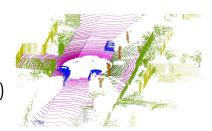
¹⁾ Cheraghian et al. Transductive zero-shot learning for 3D point cloud classification. WACV, 2020.

²⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

³⁾ Cheraghian et al. Mitigating the hubness problem for zero-shot learning of 3d objects. 2019.

Semantic Segmentation - Datasets and baselines

- 3 Datasets
 - Outdoor
 - SemanticKITTI¹⁾ (4 Unseen, 15 Seen)
 - Indoor
 - S3DIS²⁾ (4 Unseen, 9 Seen)
 - ScanNet³⁾ (4 Unseen, 16 Seen)





- 2 Baselines
 - \circ Based on DeViSE⁴⁾ (2D) and ZSLPC⁵⁾ (3D classification)
 - Additional bias reduction

⁵⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.



¹⁾ Behley et al. SemanticKITTI: A Dataset for Semantic Scene Understanding of LiDAR Sequences. ICCV, 2019.

²⁾ Armeni et al. 3D semantic parsing of large-scale indoor spaces. CVPR, 2016.

³⁾ Dai et al. Scannet: Richly-annotated 3d reconstructions of indoor scenes. CVPR, 2017.

⁴⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.

Experiments Semantic Segmentation - Semantic KITTI

15 seen, 4 unseen classes. Outdoor LiDAR dataset.

		ing set Classi- fier		nantic oU <i>U</i>	KITTI HmIoU
Supervised method.	s with di	ifferent le	evels o	f supe	rvision
Full supervision	$S \cup U$	$S \cup U$	59.4	50.3	54.5
ZSL backbone	S	$S \cup U$	52.9	13.2	21.2
ZSL-trivial	S	S	55.8	0.0	0.0
Generalized zero-si	hot-lear	ning met	hods		
ZSLPC-Seg ¹⁾ *	S	U	49.1	0.0	0.0
DeViSe-3DSeg ²⁾ *	S	И	49.7	0.0	0.0
ZSLPC-Seg ¹⁾	S	U	26.4	10.2	14.7
DeViSe-3DSeg ²⁾	\mathcal{S}	И	42.9	4.2	7.5
3DGenZ (ours)	\mathcal{S}	$S \cup \hat{\mathcal{U}}$	41.4	10.8	17.1

^{*}Direct, unrepaired (failing) adaptation.

¹⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

²⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.

Experiments Semantic Segmentation - Semantic KITTI

15 seen, 4 unseen classes. Outdoor LiDAR dataset.

	Train	ing set	Ser	SemanticKITTI				
	Back-	Classi-	mIoU		HmIoU			
	bone	fier	S	\mathcal{U}				
Supervised method.	s with di	ifferent le	evels of	supe	rvision			
Full supervision		$S \cup U$	59.4	50.3	54.5			
ZSL backbone	S	$S \cup U$	52.9	13.2	21.2			
ZSL-trivial	S	S	55.8	0.0	0.0			
Generalized zero-si	hot-lear	ning met	hods					
ZSLPC-Seg ¹⁾ *	S	И	49.1	0.0	0.0			
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ZSLPC-Seg ¹⁾	S	И	26.4	10.2	14.7			
DeViSe-3DSeg ²⁾	S	и	42.9	4.2	7.5			
3DGenZ (ours)	S	$\mathcal{S} \cup \hat{\mathcal{U}}$	41.4	10.8	17.1			

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Baselines

¹⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

²⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.

Experiments Semantic Segmentation - Semantic KITTI

15 seen, 4 unseen classes. Outdoor LiDAR dataset.

	Train	ing set	SemanticKITTI				
		Classi- fier	mI S	oU U	HmIoU		
Supervised method	s with di	ifferent le	evels o	f supe	rvision		
Full supervision	$S \cup U$	$S \cup U$	59.4	50.3	54.5		
ZSL backbone	S	$S \cup U$	52.9	13.2	21.2		
ZSL-trivial	S	S	55.8	0.0	0.0		
Generalized zero-si	hot-lear	ning met	hods				
ZSLPC-Seg ¹⁾ *	S	u	49.1	0.0	0.0		
DeViSe-3DSeg ²⁾ *	S	и	49.7	0.0	0.0		
ZSLPC-Seg1)	S	U	26.4	10.2	14.7		
DeViSe-3DSeg ²⁾	S	\mathcal{U}	42.9	4.2	7.5		
3DGenZ (ours)	S	$S \cup \hat{\mathcal{U}}$	41.4	10.8	17.1		

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²⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.



Ours

¹⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

4 unseen, 15 seen classes

Predicted

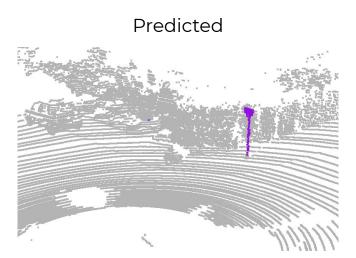


Unseen Class Bicyclist

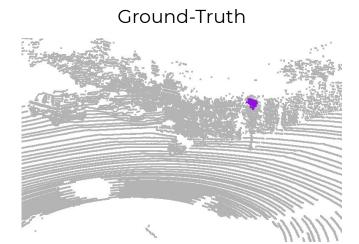
Ground-Truth



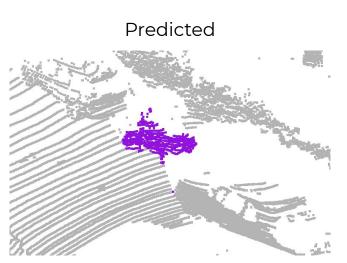
4 unseen, 15 seen classes



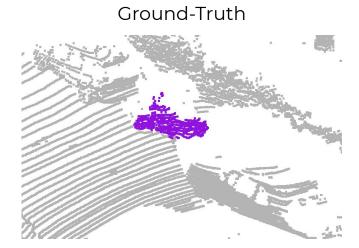
Unseen Class Traffic-Sign



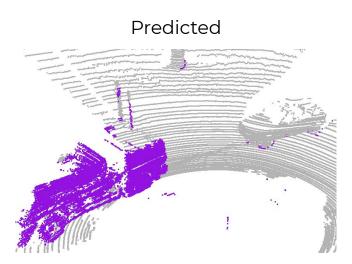
4 unseen, 15 seen classes



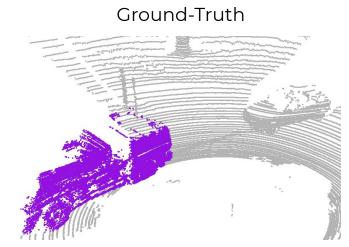
Unseen Class Motorcycle



4 unseen, 15 seen classes



Unseen Class Truck



Experiments Semantic Segmentation - S3DIS, ScanNet

	Train	ing set	1	S3D	IS		Scanl	Net	
	Back- bone	Classi- fier	mI S	oU U	HmIoU	ml S	oU U	HmIoU	
Supervised method	s with di	ifferent le	evels o	f supe	rvision			7	
Full supervision	$ S \cup U $					43.3	51.9	47.2	
ZSL backbone	S	$S \cup U$	60.9	21.5	31.8	41.5	39.2	40.3	
ZSL-trivial	S	S	70.2	0.0	0.0	39.2	0.0	0.0	
Generalized zero-s	hot-lear	ning met	hods						Bas
ZSLPC-Seg ¹⁾ *	S	И	65.5	0.0	0.0	28.2	0.0	0.0	
DeViSe-3DSeg ²⁾ *	S	U	70.2	0.0	0.0	20.0	0.0	0.0	
ZSLPC-Seg ¹⁾	S	U	5.2	1.3	2.1	16.4	4.2	6.7	
DeViSe-3DSeg ²⁾	S	\mathcal{U}	3.6	1.4	2.0	12.8	3.0	4.8	
3DGenZ (ours)	S	$S \cup \hat{U}$	53.1	7.3	12.9	32.8	7.7	12.5	

^{*}Direct, unrepaired (failing) adaptation.

¹⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

²⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.

Experiments Semantic Segmentation - S3DIS, ScanNet

	Training set		li .	S3D	IS	ScanNet			
	Back- bone	Classi- fier	mI S	oU U	HmIoU	ml S	oU U	HmIoU	
Supervised method	s with di	ifferent le	evels o	f supe	rvision				
Full supervision	$S \cup U$	$S \cup U$	74.0	50.0	59.6	43.3	51.9	47.2	
ZSL backbone	S	$S \cup U$	60.9	21.5	31.8	41.5	39.2	40.3	
ZSL-trivial	S	S	70.2	0.0	0.0	39.2	0.0	0.0	
Generalized zero-s	hot-lear	ning met	hods						
ZSLPC-Seg ¹⁾ *	S	u	65.5	0.0	0.0	28.2	0.0	0.0	
DeViSe-3DSeg ²⁾ *	S	и	70.2	0.0	0.0	20.0	0.0	0.0	
ZSLPC-Seg ¹⁾	S	u	5.2	1.3	2.1	16.4	4.2	6.7	
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Ours

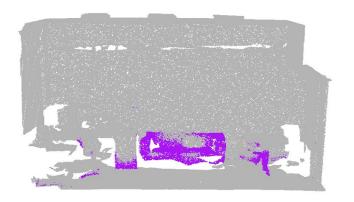
¹⁾ Cheraghian et al. Zero-shot learning of 3d point cloud objects. MVA, 2019.

²⁾ Frome et al. DeViSE: A deep visual-semantic embedding model. NIPS, 2013.

Visualisations S3DIS

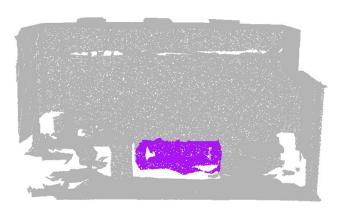
4 unseen, 9 seen classes

Predicted



Unseen Class Sofa

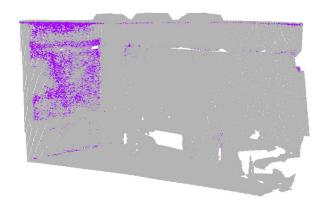
Ground-Truth



Visualisations S3DIS

4 unseen, 9 seen classes

Predicted



Unseen Class Window

ndow Ground-Truth

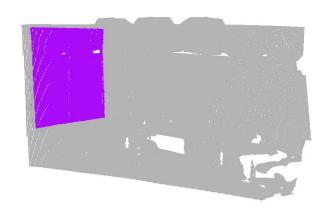
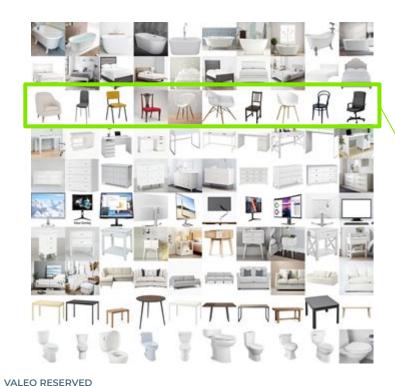


Image based 3D Zero-shot

Image-based class prototypes



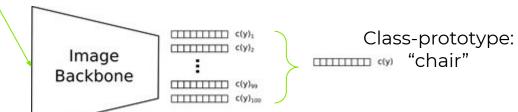
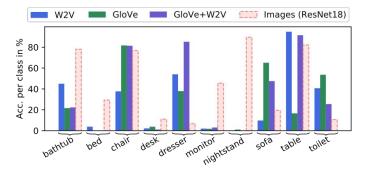


Image based 3D zero-shot - Results

Representation	Mode	assif. elNet40 GZSL	Segmentation ScanNet KITTI HmIoU		
W2V+GloVe (self-sup.)	36.8	41.3	12.5	17.1	
ResNet-18 (sup.) ResNet-50 (self-sup.)	43.6 37.0	40.0 36.5	13.9 15.5	3.6 5.3	

Only image based



Conclusion and outview

Conclusion

- 1. Reaching state of the art in **Classification** with additional bias reduction
- 2. GZSL for **Semantic Segmentation** on 3D PCs for 3 datasets:
 - a. Improving over natural baselines
 - b. Creation of a benchmark
- 3. **Image-based class prototypes** can outperform text-based ones

Outview

- Multi-Modal prototypes
- Phrasal (multi-word) embeddings to discover complex corner cases



SMART TECHNOLOGY FOR SMARTER MOBILITY