INSTITUT NATIONAL DE L'INFORMATION GÉOGRAPHIQUE ET FORESTIÈRE

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# Semantic Segmentation of 3D point Clouds


Loic Landrieu

Université Paris-Est - Machine Learning and Optimization working Group


March 2019

# Presentation

- Loic Landrieu, researcher at IGN (French Mapping Agency) in the AI department

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- **Interest:** graph-structured functional optimization and deep learning.
- **Applications:** 3D point clouds, dynamic 3D for autonomous driving, superspectral satellite images, time series, medical inverse problems.

# Presentation outline


1. Deep Learning for 3D Point Clouds
2. Learning 3D Point Clouds Segmentation
3. The Cut Pursuit Algorithm
4. Conclusion
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**credit:** medium, VisionSystemDesign, microsoft

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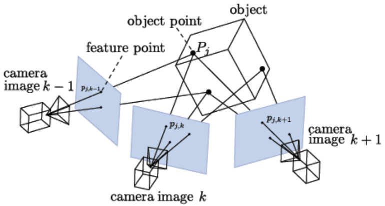


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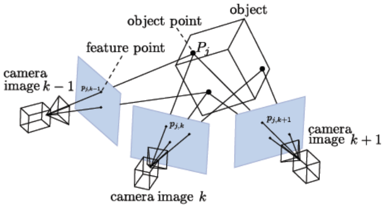



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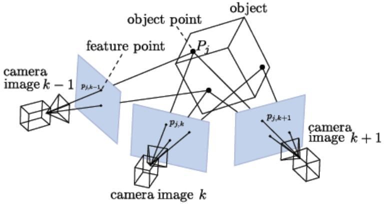



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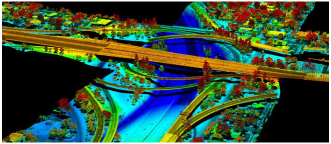

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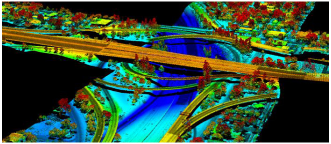
- Large acquisition: $n$ typically in the $10^8$s.



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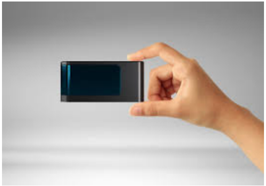

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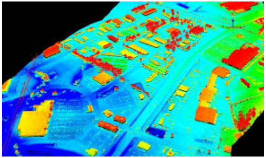

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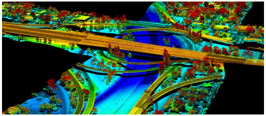

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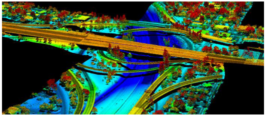

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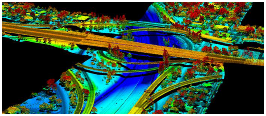
- Rapid progress in harware and methodology + major applications = **a booming field.**



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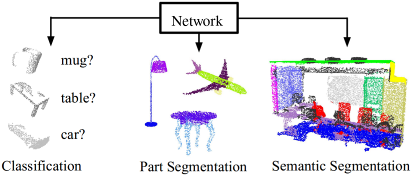


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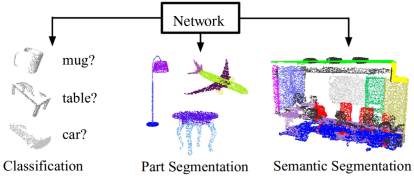


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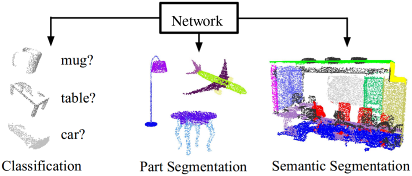


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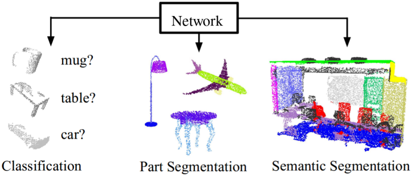


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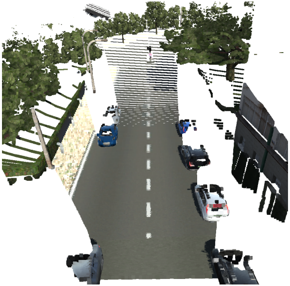

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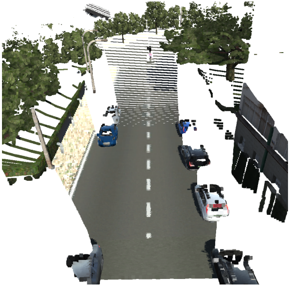

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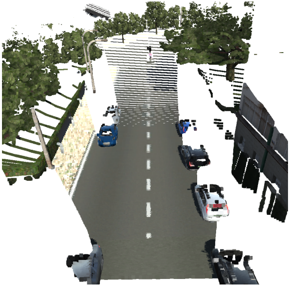

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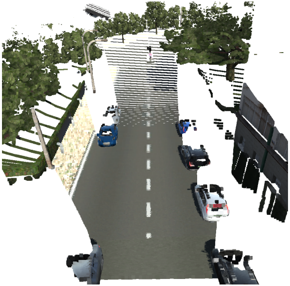

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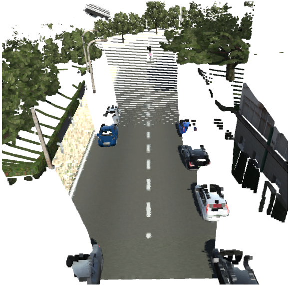

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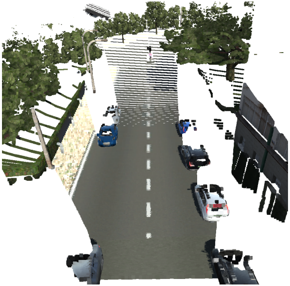

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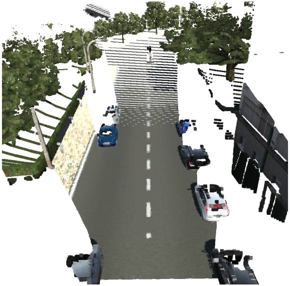

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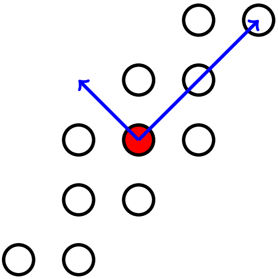
- **Step 1:** compute point features based on neighborhood



$$\text{Lin} = \frac{\sqrt{\lambda_1} - \sqrt{\lambda_2}}{\sqrt{\lambda_1}}$$

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Demantke2011

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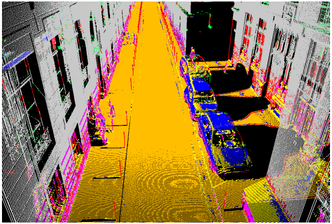

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## Pointwise classification

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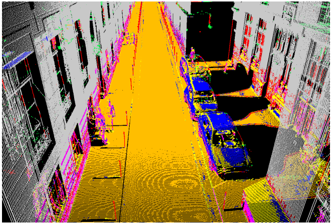

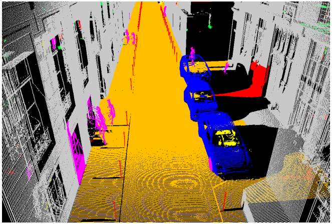

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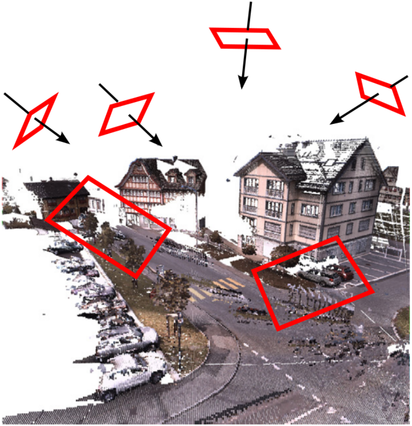

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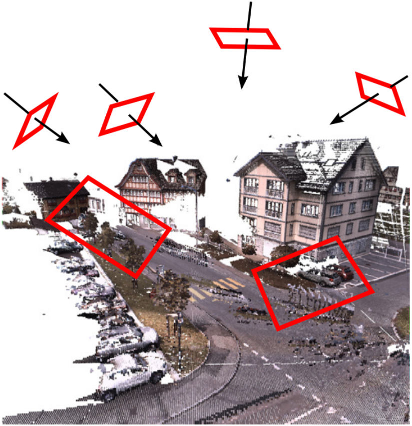

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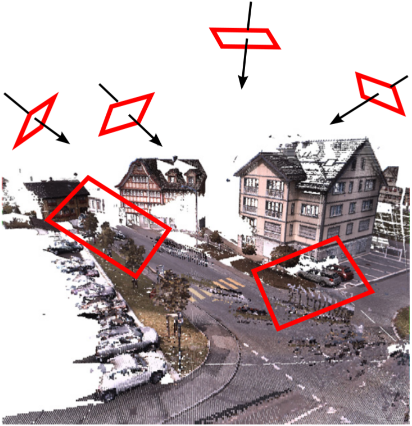

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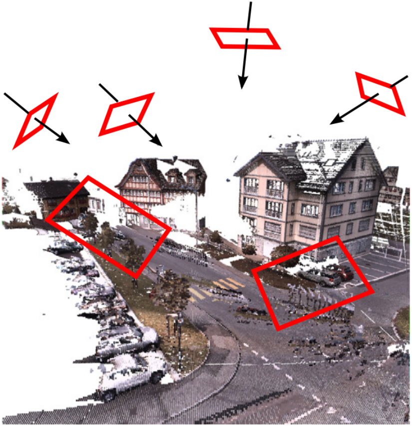

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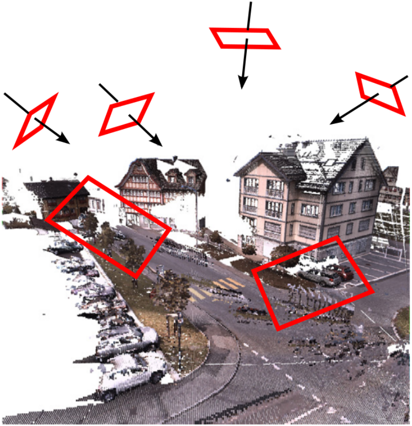

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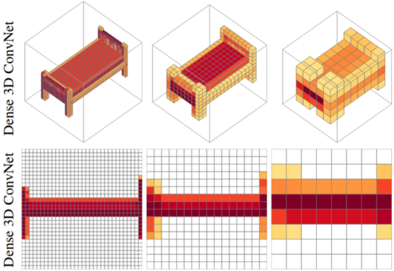


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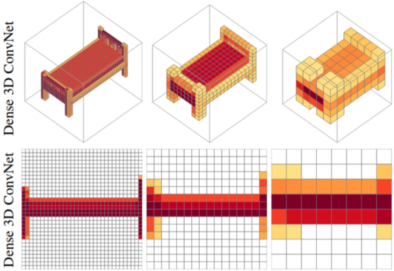


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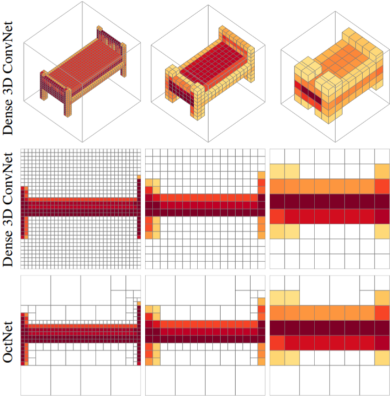


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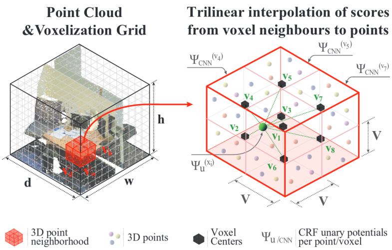


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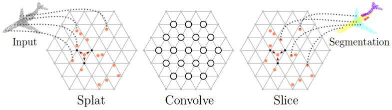


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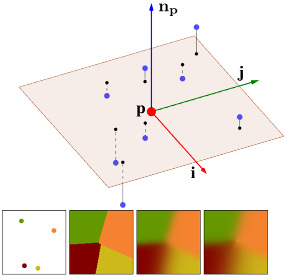


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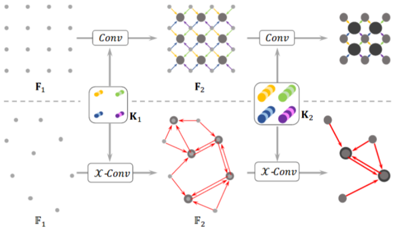


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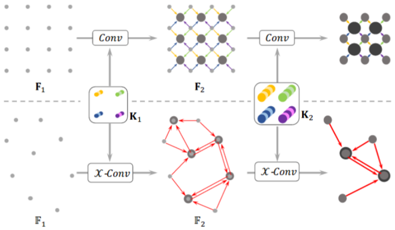


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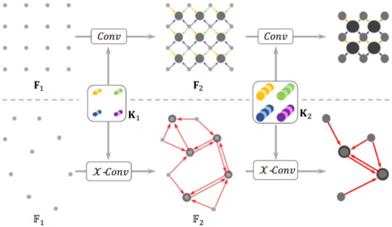
- The invariance is learnt!




Tatarchenko2018 , Li2018.

**credit:** Tatarchenko2018, Li2018

## PointNet

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Qi et. al.2017a

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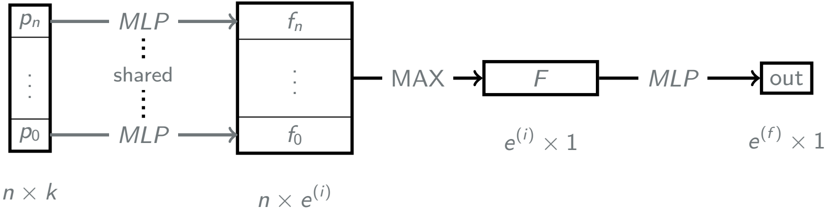
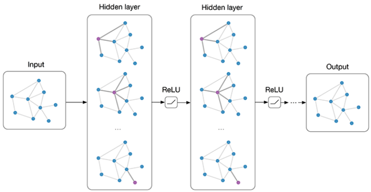
- $n$: number of points, $k$ size of observations, $e^{(i)}$ size of intermediary embeddings, $e^{(f)}$ size of output




Qi et. al.2017a

# Graph-Neural Network

- Generalize convolutions to the general graph setting.



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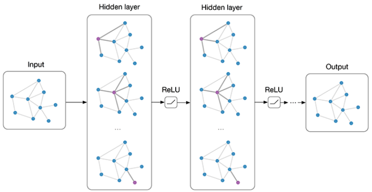


Qi2017, Simonovski2017

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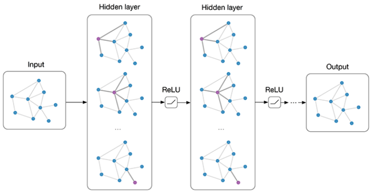


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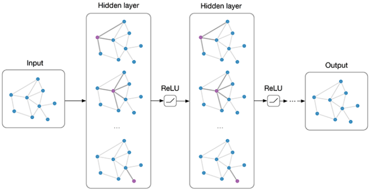


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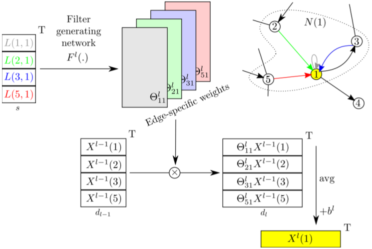
- ECC **Simonovski2017** messages are conditioned by edge features:

$$h_i^{(t+1)} = g(\sum_{j \to i} \Theta_{i,j} \odot h_j^t, h_i^t)$$




Qi2017, Simonovski2017

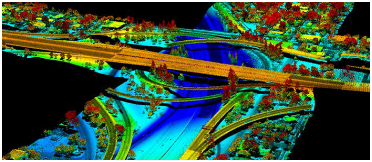
**credit:** Simonovski2017

## Presentation Layout


1. **Deep Learning for 3D Point Clouds**
   - Presentation of the Problem
   - Traditional Approaches
   - First Deep-Learning Approaches
   - Scaling Segmentation
2. **Learning 3D Point Clouds Segmentation**
3. **The Cut Pursuit Algorithm**
4. **Conclusion**
5. **Bibliography**

# Why we need to scale

- **Problem:** best approaches are very memory-hungry and the data volumes are huge.



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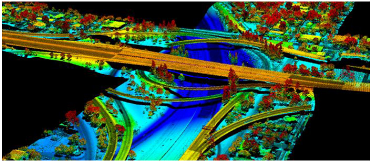

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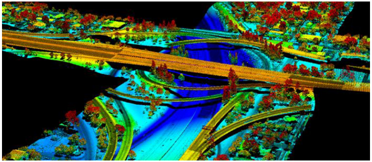

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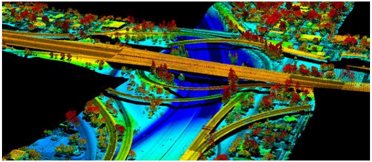
- **Sliding windows**: loses the global structure.



**credit:** tuck mapping solution

# PointNet++

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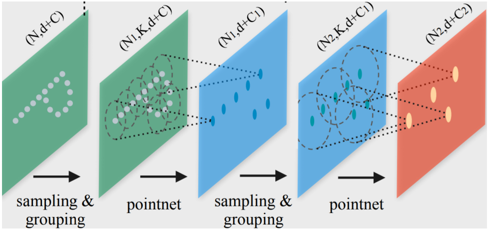


Qi et. al.2017b

**credit:** Qi et. al.2017b

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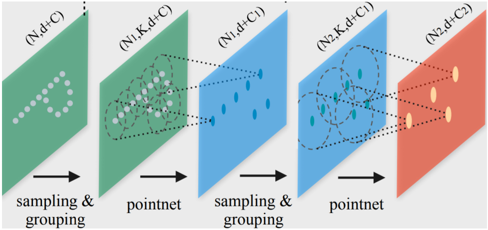


Qi et. al.2017b

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# PointNet++

- Pyramid structure for multi-scale feature extraction.
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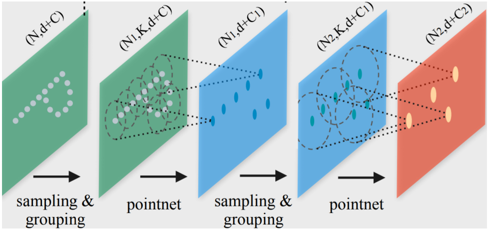
- Still require to process millions of points.

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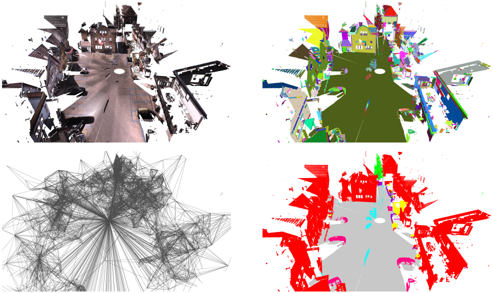

Landrieu&Simonovski2018

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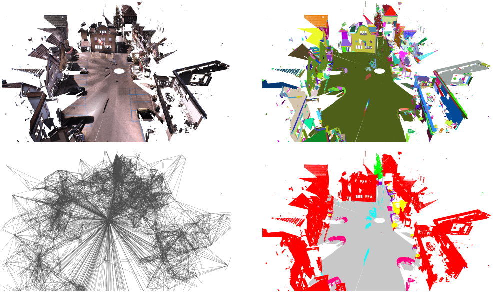

Landrieu&Simonovski2018

# SuperPoint-Graph

- **Observation:**
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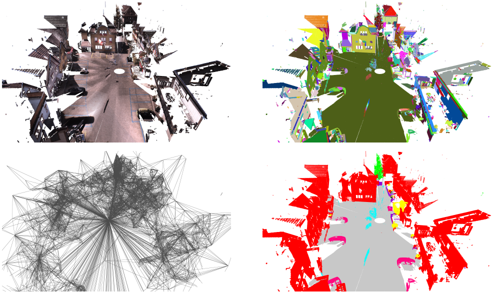
- Partition scene into superpoints with simple shapes.
- Only a few superpoints, context leveraging with powerful graph methods.



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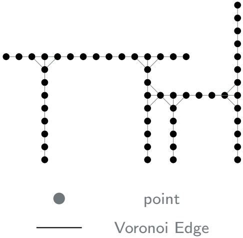
- **Contextual Segmentation:** using the global structure

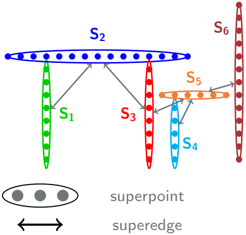
  Complexity: very low (superpoint graph $\sim$ 1000 sp)

  Algorithm: ECC with Gated Recurrent Unit (GRU)

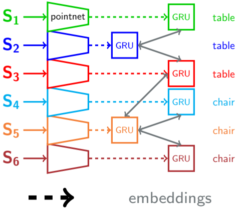
## Pipeline




(a) Point cloud



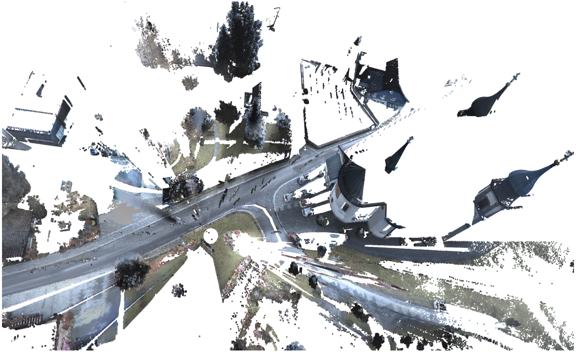

(b) Superpoint graph




(c) Convolution Network

# Qualitative Results: Semantic3D

Semantic3D: 3 billions points over 30 clouds



- route
- herbe
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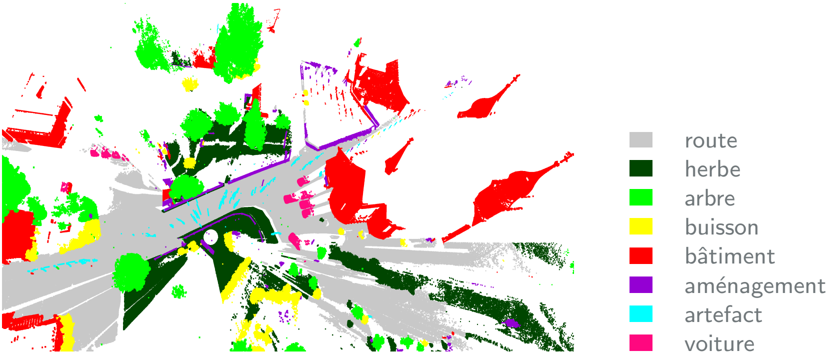

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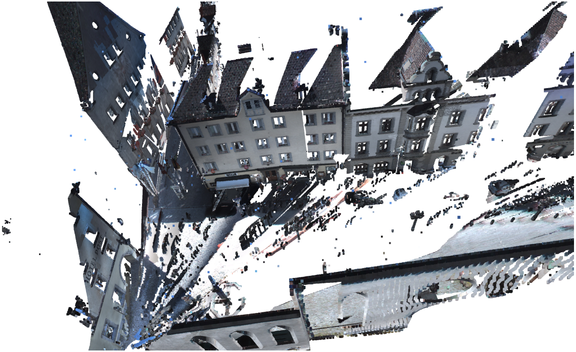

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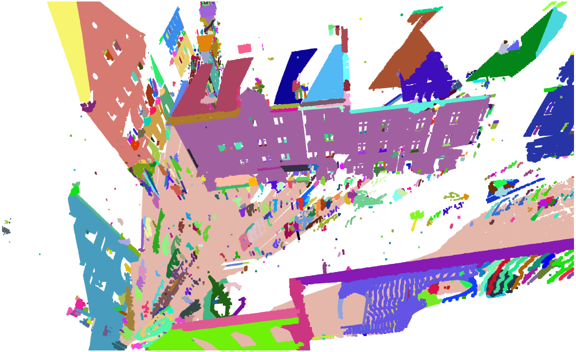

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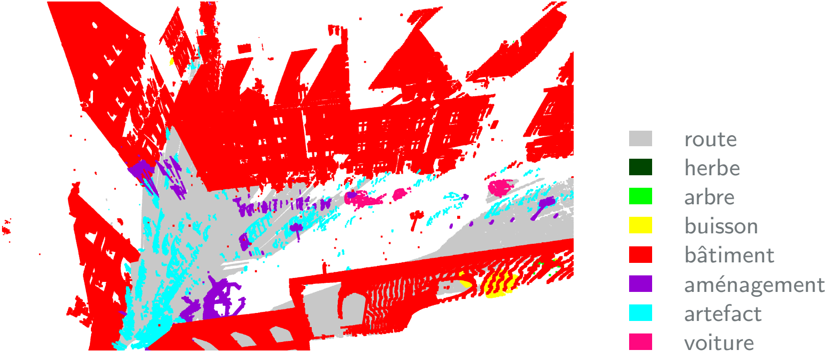

# Quantitative Results: Semantic3D

| **Methode** | OA | mIoU | road | grass | tree | bush | build-ing | hard-scape | arti-fact | cars |
|---|---|---|---|---|---|---|---|---|---|---|
| reduced test set: 78 699 329 points | | | | | | | | | | |
| TMLC-MSR | 86.2 | 54.2 | 89.8 | 74.5 | 53.7 | 26.8 | 88.8 | 18.9 | 36.4 | 44.7 |
| DeePr3SS | 88.9 | 58.5 | 85.6 | 83.2 | 74.2 | 32.4 | 89.7 | 18.5 | 25.1 | 59.2 |
| SnapNet | 88.6 | 59.1 | 82.0 | 77.3 | 79.7 | 22.9 | 91.1 | 18.4 | 37.3 | 64.4 |
| SegCloud | 88.1 | 61.3 | 83.9 | 66.0 | 86.0 | 40.5 | 91.1 | 30.9 | 27.5 | 64.3 |
| SPG (Ours) | **94.0** | **73.2** | **97.4** | **92.6** | **87.9** | **44.0** | **93.2** | **31.0** | **63.5** | **76.2** |
| full test set: 2 091 952 018 points | | | | | | | | | | |
| TMLC-MS | 85.0 | 49.4 | 91.1 | 69.5 | 32.8 | 21.6 | 87.6 | 25.9 | 11.3 | 55.3 |
| SnapNet | 91.0 | 67.4 | 89.6 | **79.5** | 74.8 | 56.1 | 90.9 | 36.5 | 34.3 | 77.2 |
| SPG (Ours) | **92.9** | **76.2** | **91.5** | 75.6 | **78.3** | **71.7** | **94.4** | **56.8** | **52.9** | **88.4** |

# Qualitative Results: S3DIS

Indoor, 3 buildings, 6 stories, 200+ rooms, 600 000 000+ points

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- column
- beam
- window
- door
- table
- chair
- bookcase
- board
- other

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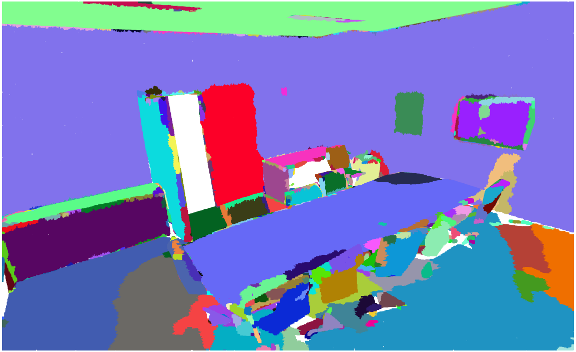

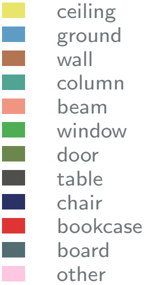

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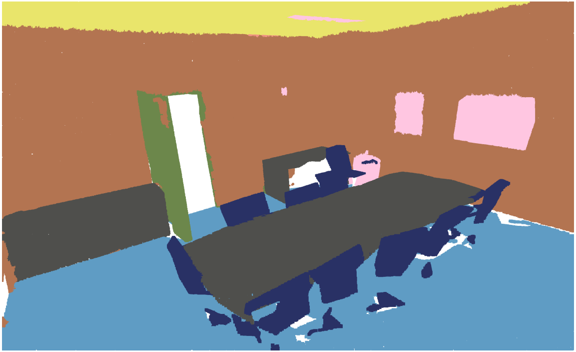

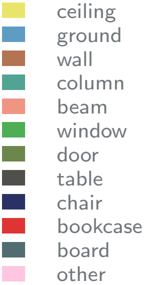

# Résultats qualitatif: S3DIS

## Quantitative Results: S3DIS

| **Method** | OA | mAcc | mIoU | door | board |
|---|---|---|---|---|---|
| A5 PointNet | – | 48.5 | 41.1 | 10.7 | **26.3** |
| A5 SEGCloud | – | 57.3 | 48.9 | 23.1 | 13.0 |
| **A5 SPG** | 86.4 | **66.5** | **58.0** | **61.5** | 2.1 |
| PointNet | 78.5 | 66.2 | 47.6 | 51.6 | 29.4 |
| Engelmann | 81.1 | 66.4 | 49.7 | 51.2 | **30.0** |
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| Śtep | Full cloud | 2 cm | 3 cm | 4 cm |
|---|---|---|---|---|
| Voxelisation | 0 | 40 | 24 | 16 |
| Features | 439 | 194 | 88 | 43 |
| Partition | 3428 | 1013 | 447 | 238 |
| SPG computation | 3800 | 958 | 436 | 252 |
| Inference $\times 10$ | 240 | 110 | 60 | 50 |
| Total | 7907 | 2315 | 1055 | 599 |
| mIoU 6-fold | 54.1 | 60.2 | 62.1 | 57.1 |

## Superpoint Partition

$$f^\star = \underset{f\in\mathbb{R}^{C\times m}}{\arg\min} \sum_{i\in C} \|f_i - e_i\|^2 + \sum_{(i,j)\in E} w_{i,j}\,[f_i \neq f_j]\,,$$

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- Superpoints: connected components of a piecewise constant approximation of $e$ structured by an adjacency graph.

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- $e \in \mathbb{R}^{C\times m}$ : handcrafted descriptors of the local geometry/radiometry
- Superpoints: connected components of a piecewise constant approximation of $e$ structured by an adjacency graph.
- **Problem:** any errors made in the partition will carry in the prediction...

# Presentation Layout


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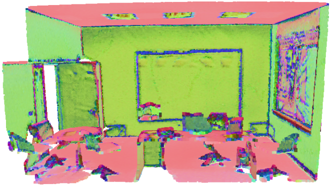
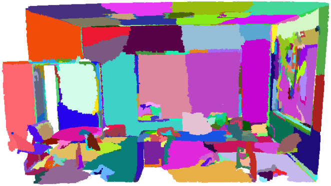
# The Pipeline

Input Point Cloud



Learned Embedding



Oversegmentation

True Objects

**General idea:**

1) Train a neural network to produce points embeddings with high contrast at the border of objects...

2) ... Which serve as inputs of a **nondifferentiable** segmentation algorithm.

# Adjacency Graph

- $G = (C, E)$ a meaningful adjacency graph

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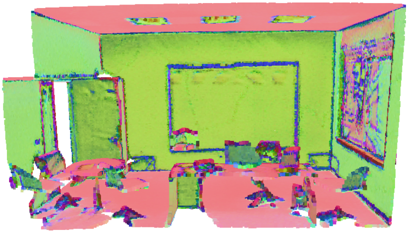
- We want embeddings with high contrast at $E_{\text{inter}}$ and similar value at $E_{\text{intra}}$



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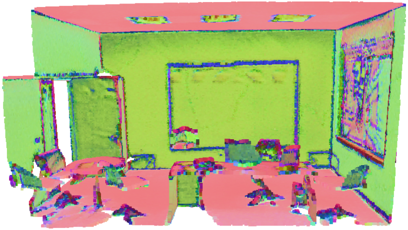

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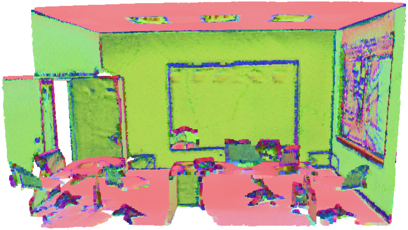
  almost!



# Generalized Minimal Partition Problem

- $e_i$ embeddings of the local geometry/radiometry

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- **Idea:** Superpoints are the component of a **piecewise-constant approximation** of the embedings

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- Good approximations can be computed with $\ell_0$-cut pursuit [Landrieu & Obozinski SIIMS 2018]

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- To backpropagate we need: $\frac{\partial CCC}{\partial f^\star}$ and $\frac{\partial f^\star}{\partial e}$
- **Problem:**Those functions are **not backpropagable**.

## Graph-Structured Contrastive Loss

- We propose a *surrogate* loss to learn meaningful embeddings

$$\ell(e) = \frac{1}{|E|}\left(\sum_{(i,j)\in E_{\text{intra}}} \phi\left(e_i - e_j\right) + \sum_{(i,j)\in E_{\text{inter}}} \mu_{i,j}\psi\left(e_i - e_j\right)\right),$$

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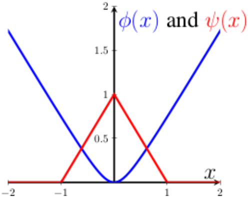
- $\phi$ minimum at 0, $\psi$ maximum at 0

$$\begin{aligned}\phi(x) &= \delta(\sqrt{\|x\|^2/\delta^2+1}-1)\\ \psi(x) &= \max\left(1-\|x\|,0\right)\end{aligned}$$



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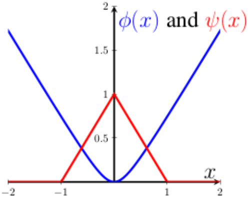

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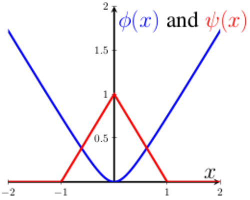
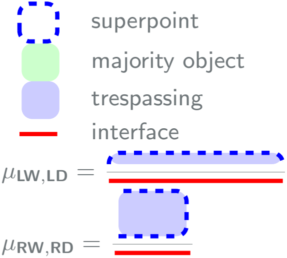
- $\mu_{i,j}$ : weight of inter-edges

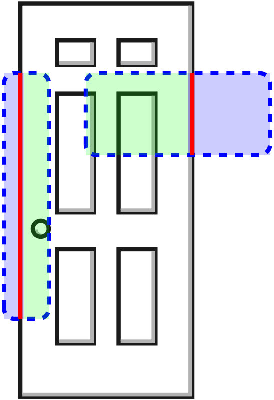


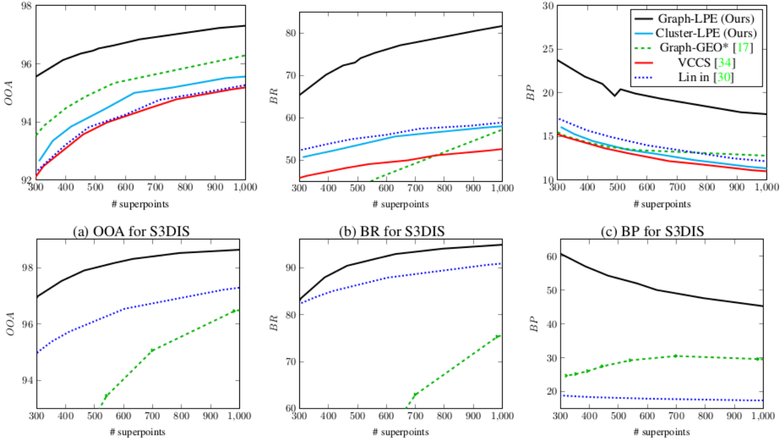
## Cross-Partition Weighting Strategy, cont'd

$$\mu_{U,V} = \mu \frac{\min(|U|, |V|)}{|(U,V)|} \quad \text{for } (U,V) \in \mathcal{E} \qquad \mu_{i,j} = \mu_{U,V} \text{ for all } (i,j) \in (U,V)$$

- Role of $\mu_{i,j}$ critical: assess impact of missed edge.
- Operate on $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ adjacency graph of cross-partition between superpoints and real objects.



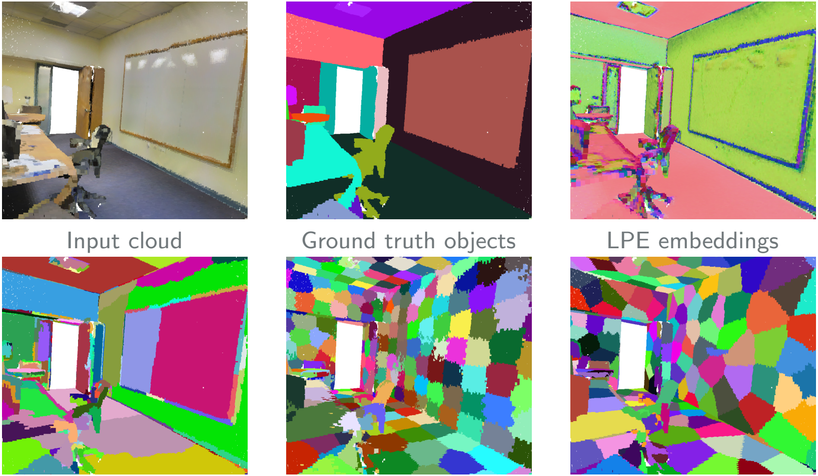



(a) OOA for S3DIS (b) BR for S3DIS (c) BP for S3DIS

(d) OOA for vKITTI (e) BR for vKITTI (f) BP for vKITTI

**We require 5 times less superpoints for similar performance!**

# Illustration



Input cloud | Ground truth objects | LPE embeddings

Graph-LPE (ours) | VCCS, Papon *et al.* 2013 | Lin *et al.* 2018

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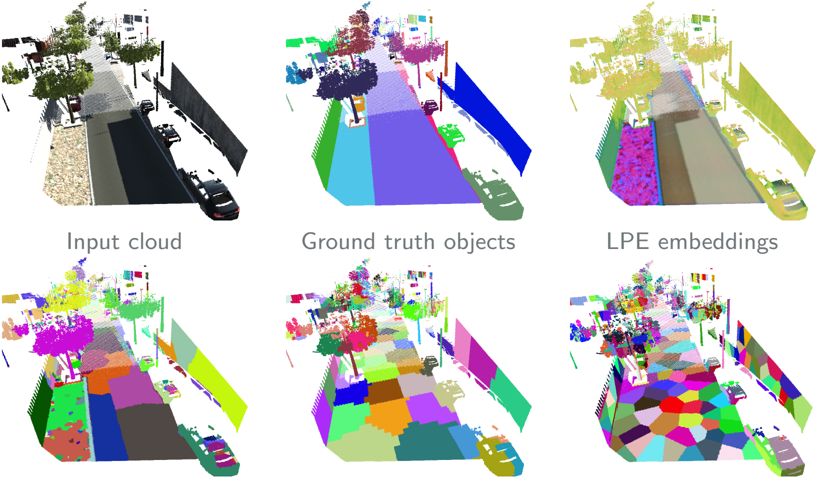

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## Results

| **Method** | OA | mAcc | mIoU |
|---|---|---|---|
| 6-fold cross validation | | | |
| PointNet 2017 | 78.5 | 66.2 | 47.6 |
| Engelmann *et al.* in 2017 | 81.1 | 66.4 | 49.7 |
| PointNet++ 2017 | 81.0 | 67.1 | 54.5 |
| Engelmann *et al.* in 2018 | 84.0 | 67.8 | 58.3 |
| SPG 2018 | 85.5 | 73.0 | 62.1 |
| PointCNN 2018 | **88.1** | 75.6 | 65.4 |
| Graph-LPE + SPG (ours) | 87.8 | **77.5** | **67.6** |
| Fold 5 | | | |
| PointNet 2017 | - | 49.0 | 41.1 |
| Engelmann *et al.* in 2018 | 84.2 | 61.8 | 52.2 |
| pointCNN 2018 | 85.9 | 63.9 | 57.3 |
| SPG 2018 | 86.4 | 66.5 | 58.0 |
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**Table:** S3DIS

| **Method** | OA | mAcc | mIoU |
|---|---|---|---|
| PointNet 2017 | 79.7 | 47.0 | 34.4 |
| Engelmann 2018 | 79.7 | 57.6 | 35.6 |
| Engelmann 2017 | 80.6 | 49.7 | 36.2 |
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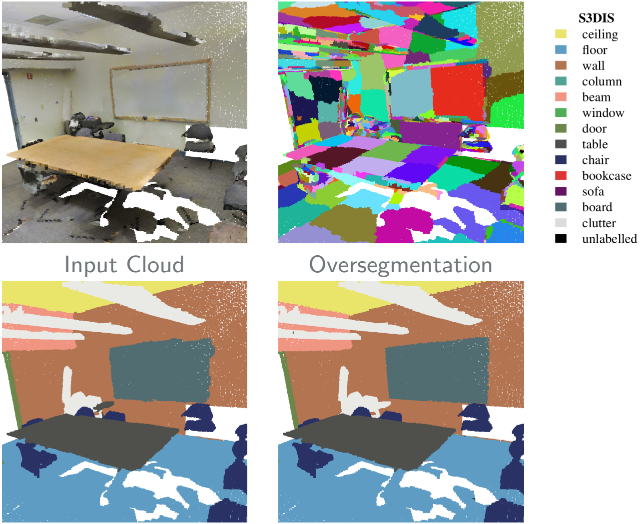
**Table:** vKITTI

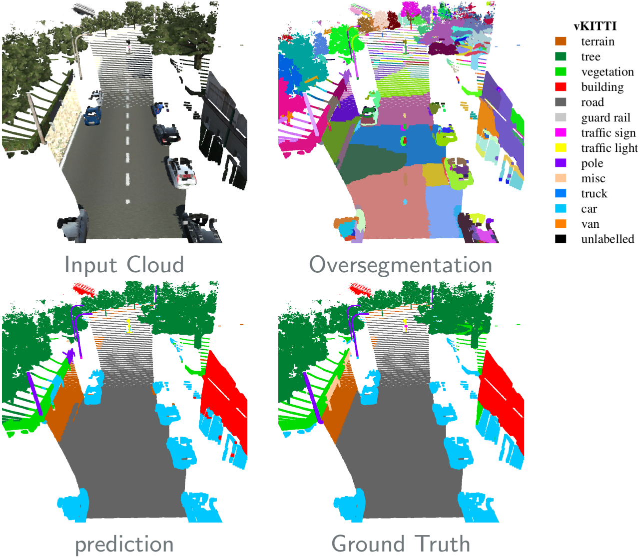
# Illustration




Input Cloud | Oversegmentation

prediction | Ground Truth

# Illustration



# Presentation Layout


1. Deep Learning for 3D Point Clouds
2. Learning 3D Point Clouds Segmentation
3. **The Cut Pursuit Algorithm**
4. Conclusion
5. Bibliography

# the Cut-Pursuit Algorithm

- A working-set approach to graph-structured spatial regularization

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- **Main Idea:** exploiting the coarseness of the solutions of such problem.

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# Objective

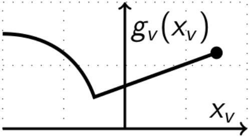
$$x^\star = \arg\min_{x \in \mathbb{R}^V} f(x) + \sum_{v \in V} g_v(x) + \sum_{(u,v) \in E} w_{(u,v)} |x_u - x_v|$$

differentiable

dir. derivative in $]-\infty, \infty]$
ex: $|\cdot|, \iota_\Omega(\cdot)$

graph total variation

- Optimization problem strutured by $G = (V, E, w)$



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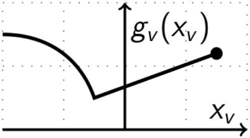

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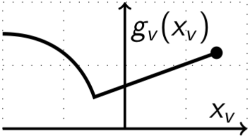
- Includes inverse problems: $f(x) = \|Ax - y\|^2$



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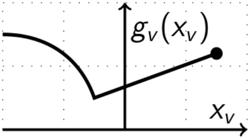

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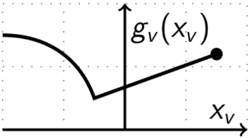

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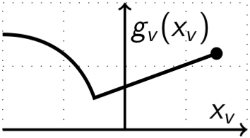
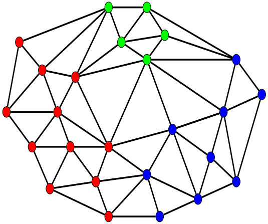


# Motivation

- TV regularization ⇒ solution piecewise constant.



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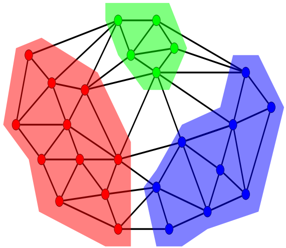

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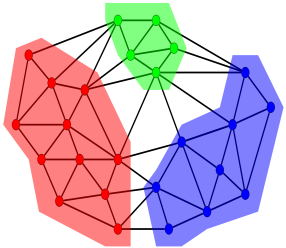
- TV regularization ⇒ solution piecewise constant.
- What if we knew this partition in advance?



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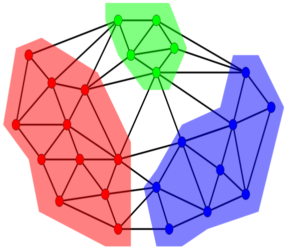
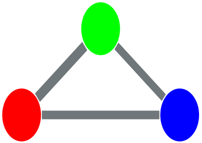
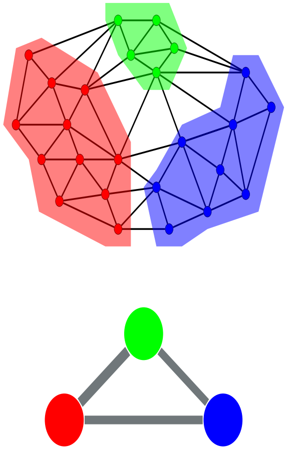
- TV regularization ⇒ solution piecewise constant.
- What if we knew this partition in advance?
- We could solve the problem on a much smaller **reduced graph**.





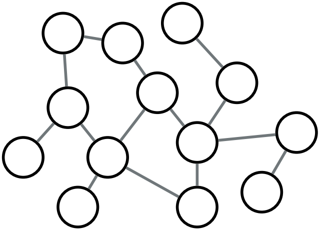
## Motivation

- TV regularization $\Rightarrow$ solution piecewise constant.
- What if we knew this partition in advance?
- We could solve the problem on a much smaller **reduced graph**.
- TV regularization constrained to piecewise constant solutions wrt a partition of $G \Leftrightarrow$ TV regularization wrt. the reduced graph.



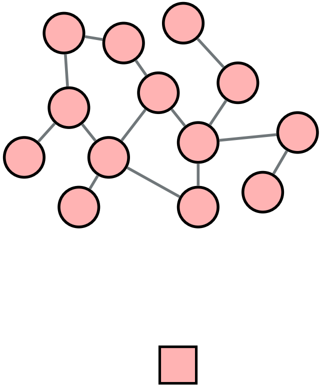
## Principle

1 • Start with a trivial partition $P = \{V\}$



## Principle

1. Start with a trivial partition $P = \{V\}$
2. Solve problem on reduced graph induced by $P$



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1. Start with a trivial partition $P = \{V\}$
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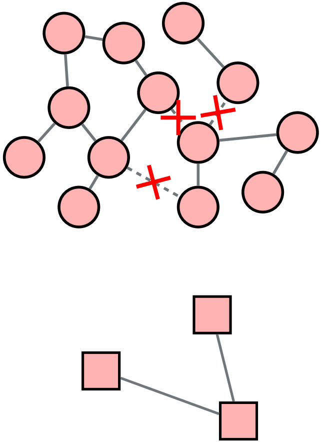

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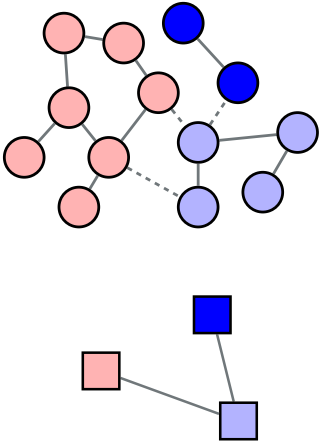

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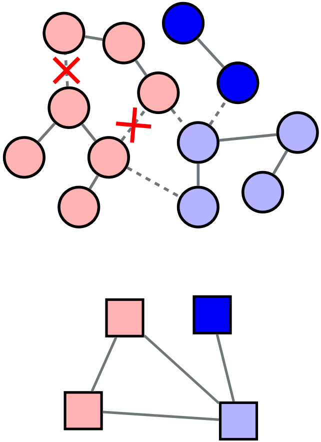

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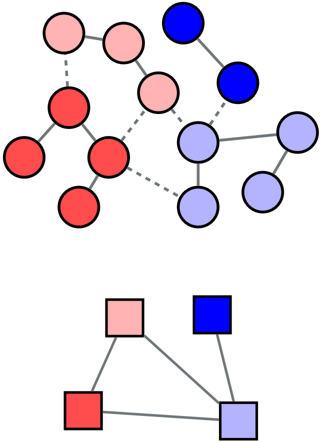

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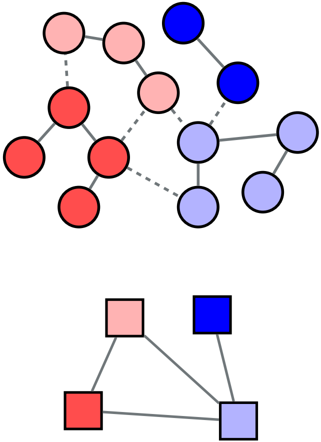

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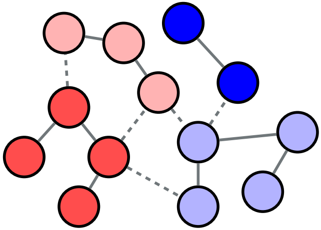

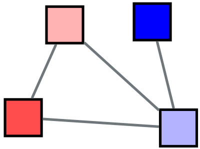

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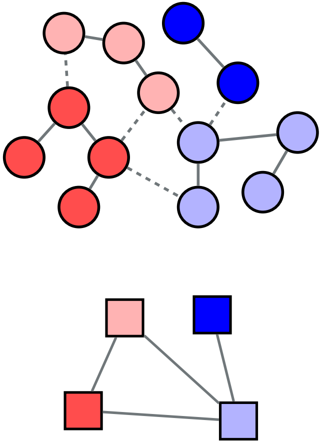

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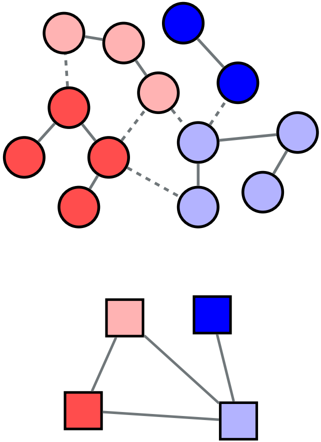
- Provable convergence in finite number of steps.
- In practice only a few iterations necessary.



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- **In practice:** pick steepest direction in finite set $D^V$:

**Direction set:**

smooth case ($g_v = 0$ for all $v \in V$): $D = \{-1, +1\}$
nonsmooth case: $D = \{-1, 0, +1\}$
Steepest direction as a graph cut problem.

## Implementation and variants

- Reduced problem: proximal algorithm (Preconditoned Forward Douglas-Rachford) on **reduced graph**

H. Raguet and L. Landrieu. Preconditioning of a Generalized Forward-Backward Splitting and Application to Optimization on Graphs. SIAM Journal on Imaging Sciences, 2015.

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## EEG Experiment

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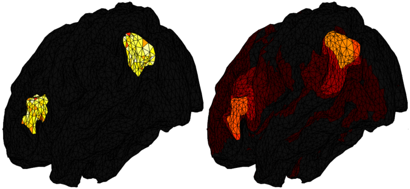

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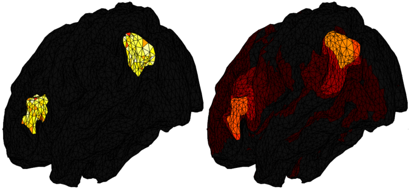

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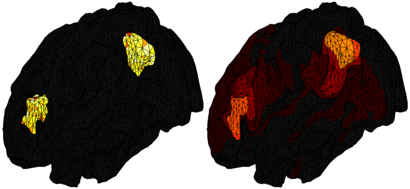

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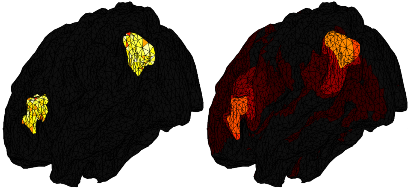

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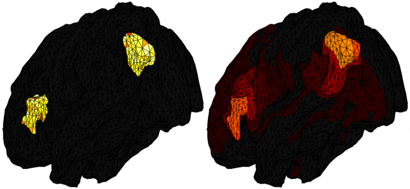

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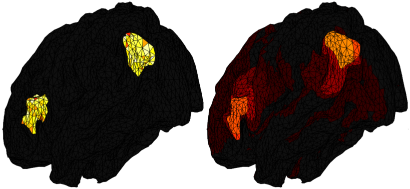
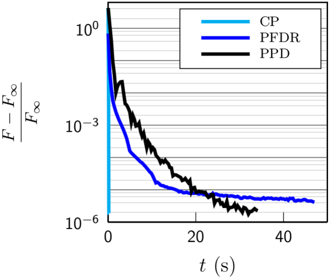
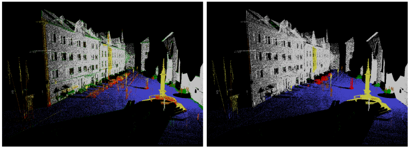




# Semantic Segmentation Experiment

- Spatial Regularization of pointwise probabilistic semantic segmentation $q$ (from local context)



(b) Random forest predictions (c) Regularization

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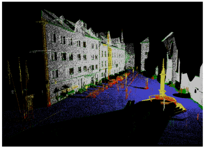

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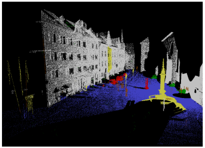

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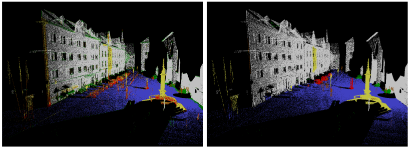

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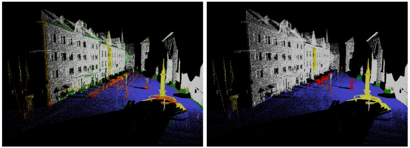

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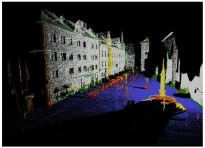

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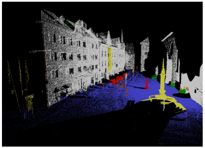

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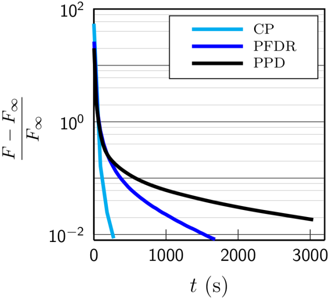

# Presentation Layout


1. Deep Learning for 3D Point Clouds
2. Learning 3D Point Clouds Segmentation
3. The Cut Pursuit Algorithm
4. Conclusion
5. Bibliography

# Conclusion

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  - Use neural networks to learn the inputs and parameters of efficient optimization algorithms.
  - Use graph-structured optimization to compute the structure of neural network adapted to the data.
- All our work is online:
  - `loicland/superpoint-graph` 252 ★ 75
  - `loicland/cut-pursuit` 22 ★ 7
  - `1a7r0ch3/parallel-cut-pursuit` very soon!

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# Bibliography I

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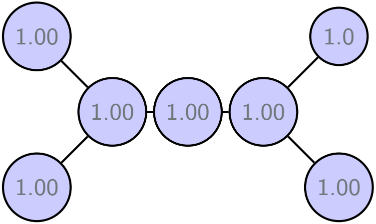
## Non-differentiability of the naive pipeline

- Non differentiability of the CCC operator



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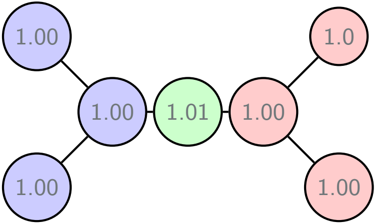
= Tiny changes - large consequence



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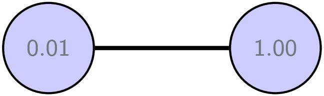


$$f_0^\star = 0.505, \quad f_1^\star = 0.505$$

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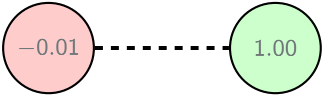
= non-continuous w.r.t inputs




$$f_1^\star = -0.01, \quad f_1^\star = 1.00$$