JURSE 2019
VANNES-FRANCE

Deep Learning for Remote Sensing Tutorial

Presentation outline

Presentation Layout

- Researcher at ONERA (French Aerospace Laboratory), Univ. Paris Saclay
- **Focus:** deep learning for remote sensing, robotics and perception

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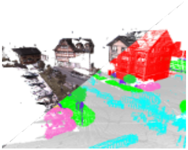
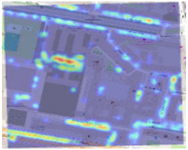
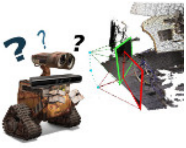
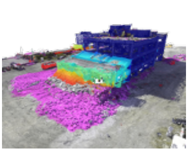

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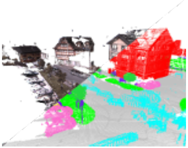
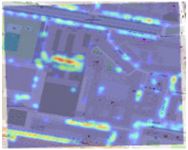
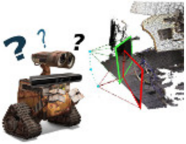
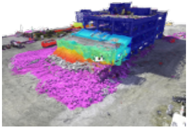

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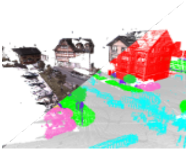
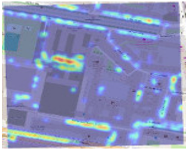
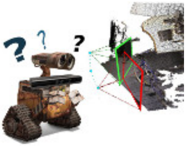
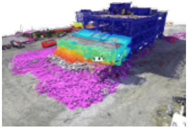
- Web: https://blesaux.github.io/

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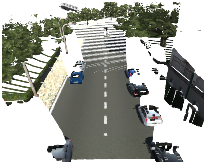
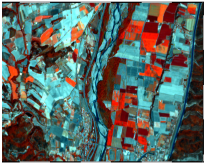
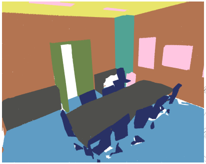
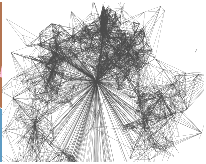

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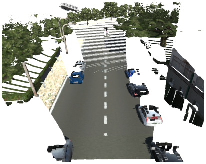
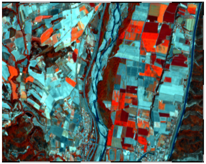
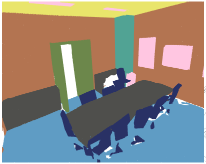
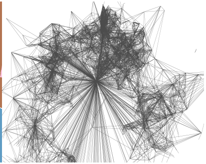

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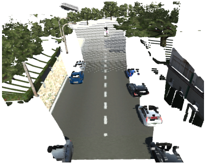
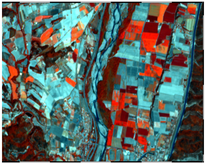
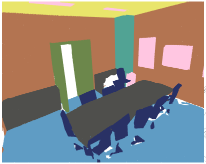
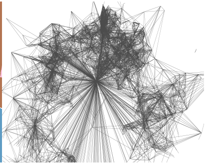

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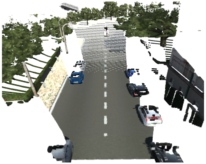
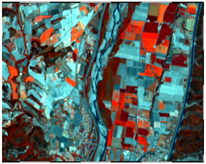
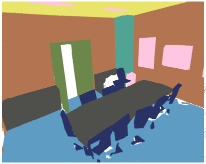
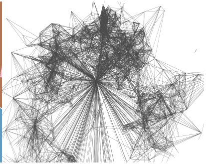

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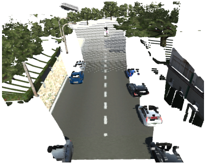
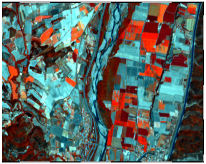
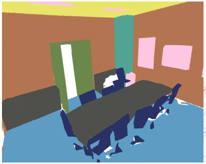
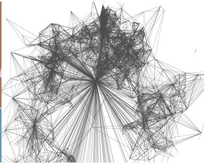

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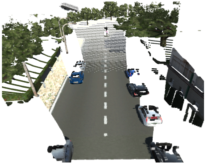
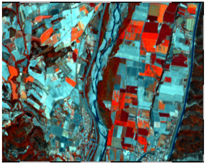
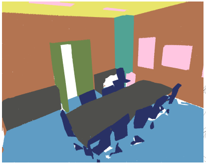
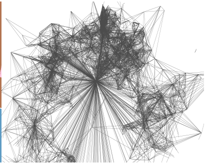
- Superspectral satellite imagery time-sequences analysis.

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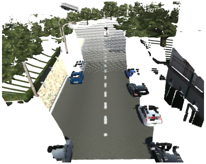
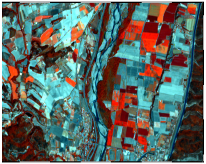
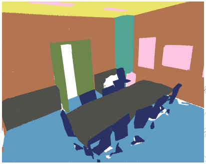
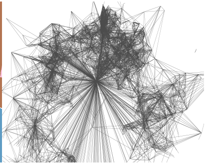
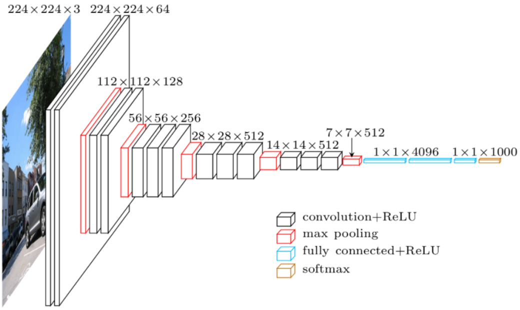
- Learning on huge graphs.

Presentation Layout

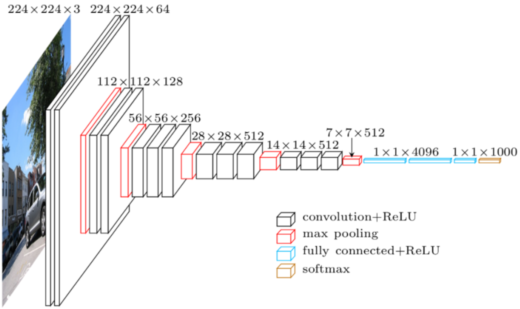
- **Motivation:** sufficient data trumps expertise.



credit : jeremyjordan.me

Deep Learning basics

- **Motivation:** sufficient data trumps expertise.
- **Main idea:** replace all handcrafted features (SIFTs, HOGs, etc...) with learned ones.



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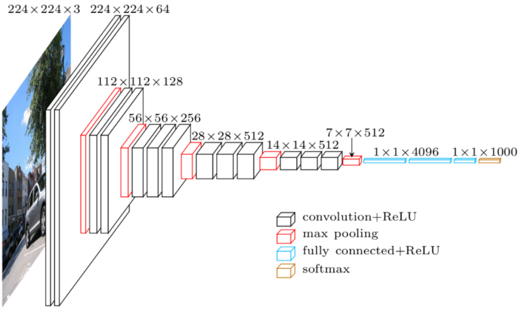
- **Motivation:** sufficient data trumps expertise.
- **Main idea:** replace all handcrafted features (SIFTs, HOGs, etc...) with learned ones.
- Each unit (or neuron) is simple, the network architecture is complex.



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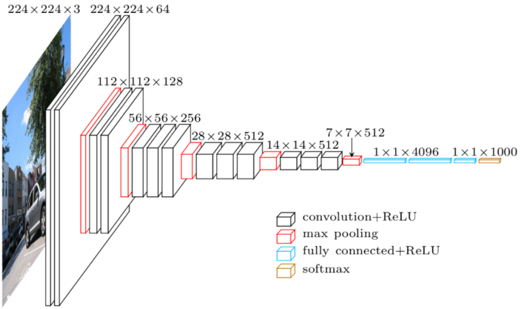

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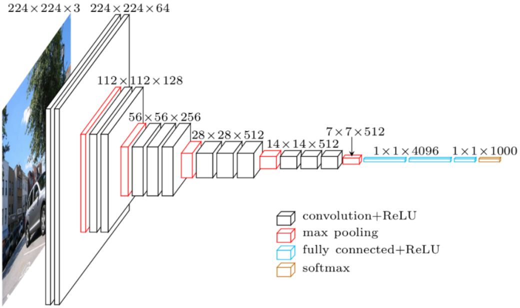
- Each unit (or neuron) is simple, the network architecture is complex.
- The network architecture must represent the structure of the data.
- **AT NO POINT ARE ARTIFICIAL NEURAL NETWORKS SUPPOSED TO MODEL AN ACTUAL NEURON/BRAIN.**



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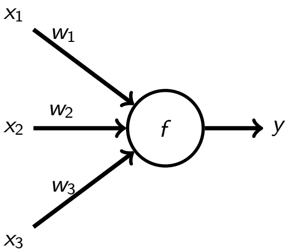
Artificial Neuron

- $y = f(\sum_i w_i x_i)$
- x_i : inputs
- w_i : weights
- f : non-linearity
- y : outputs



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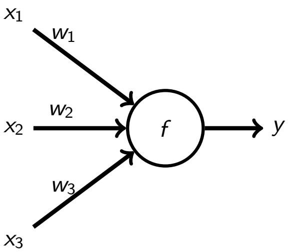
- **In short :** a matrix product $X^\intercal W$ and non-linearity.



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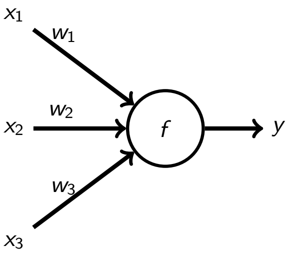
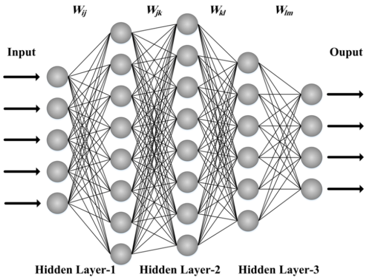
- **In short :** a matrix product $X^\intercal W$ and non-linearity.
- Non linearity essential (or else simplifies to a matrix product).

  f = sigmoid, Relu=max$(0, x)$.



Multilayer Perceptron

- Organization in layers



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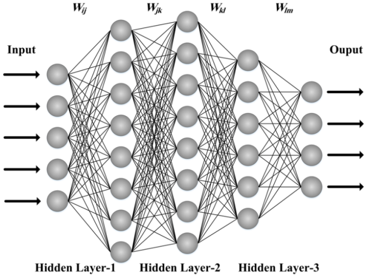
Multilayer Perceptron

- Organization in layers
- the deeper layers extracts more complicated / abstract features



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Multilayer Perceptron

- Organization in layers
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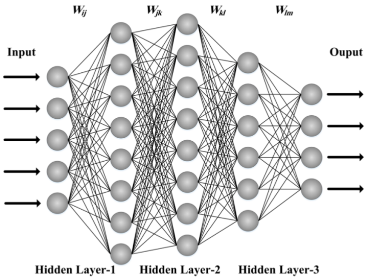
- Very old model, exists since the 50s



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Multilayer Perceptron

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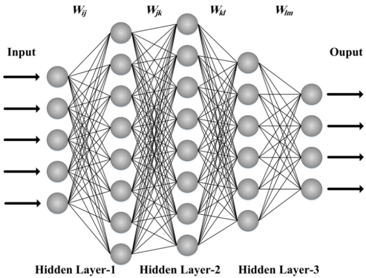
- **Universal Approximation Theorem:** any functions of x can be approximated to arbitrary precision by a MLP with sufficient width.



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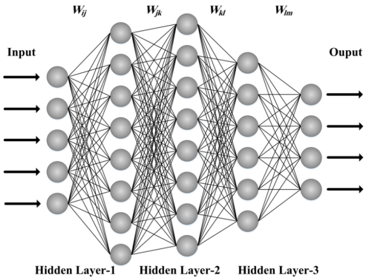
Multilayer Perceptron

- Organization in layers
- the deeper layers extracts more complicated / abstract features
- Very old model, exists since the 50s
- **Universal Approximation Theorem:** any functions of x can be approximated to arbitrary precision by a MLP with sufficient width.
- Simple model, no assumption whatsoever on the data structure.



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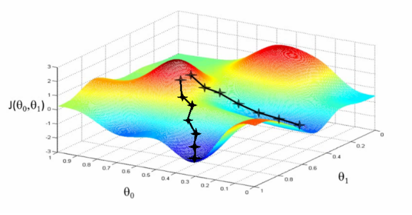
- **Training a neural network:** finding values for the weights w such that output y is close to a ground truth value $\hat{y}$.



credit : exortech.github.io

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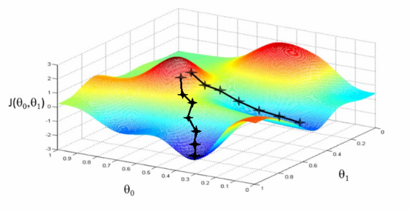
- We define a loss function $\mathcal{L}(y(w), \hat{y})$ decreasing with the precision (for example: $\|y - \hat{y}\|^2$, cross-entropy).



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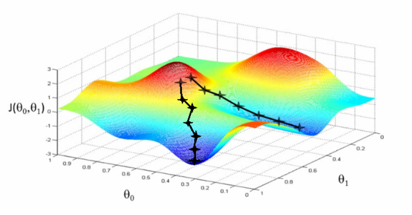

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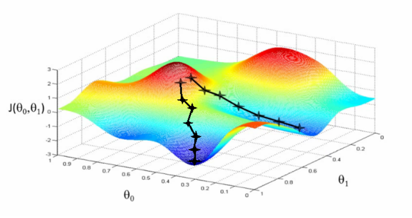

credit : exortech.github.io

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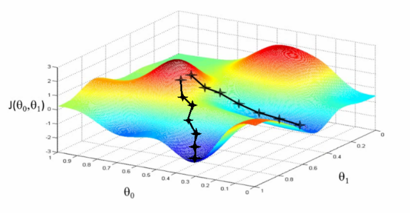

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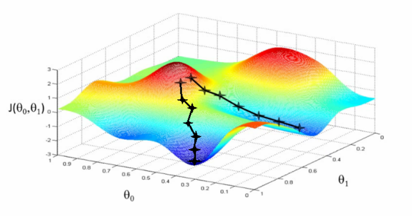
- $\mathcal{L}$ is usually an (almost) differentiable function but is generally nonconvex.
- However, we can find good weights with Stochastic Gradient Descent.
- Automatic differentiation: gradients are easily computed and propagated ("backprop").
- Supervized learning, require a lot of high quality annotations.



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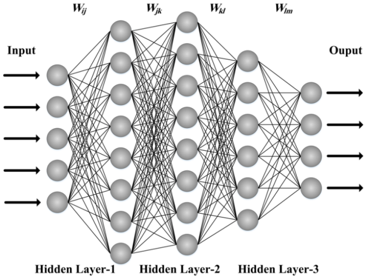

credit : pubs.sciepub.com/ajmm

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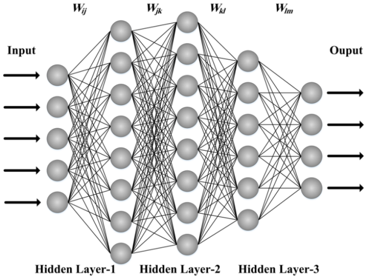
- 100×100 image : 10^8 parameters per layer! Unmanageable.



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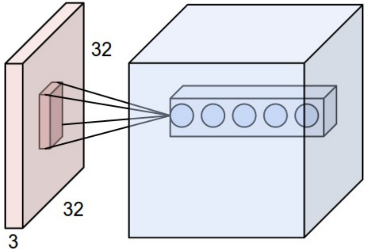

credit : cs231n.github.io

Convolutional Neural Network

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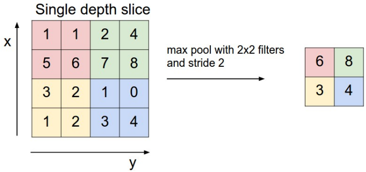

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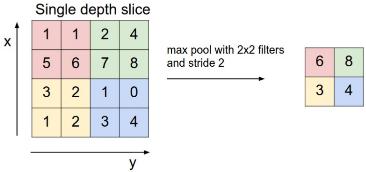
- Paired with *Pooling layers* which decrease the size of the feature maps.
- Very successful for images, exploits the spatial structure.



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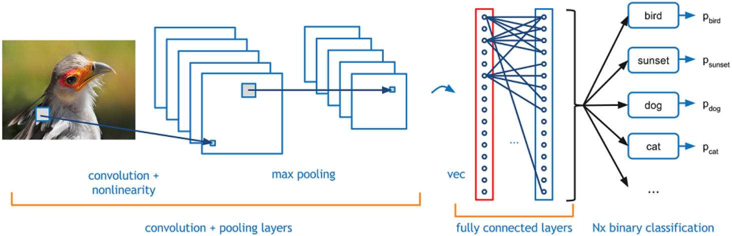
Convolutional Neural Network II



- Traditional structure:
  - Sequence of (Conv + Pool) units to compute local features and decrease embeddings size
  - One (or two) fully connected MLP at the end to analyze the whole image.

credit: adeshpande3.github.io

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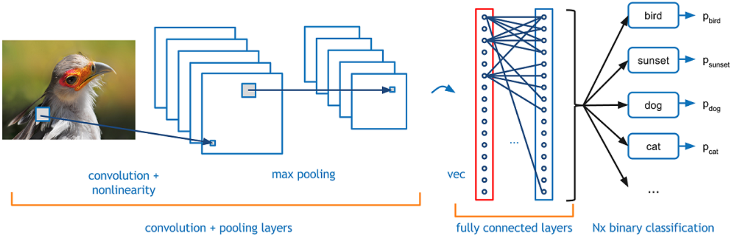

- Traditional structure:
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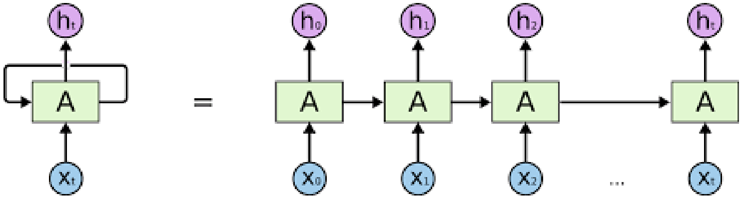
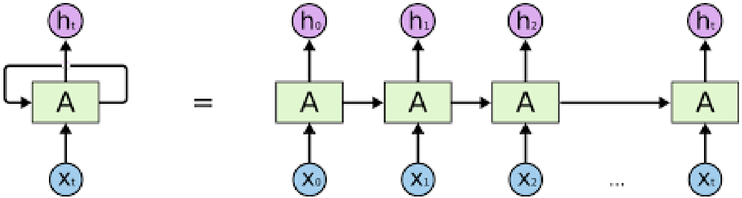
  - One (or two) fully connected MLP at the end to analyze the whole image.
  - Deep structures seem to work best.

credit: adeshpande3.github.io

Recurrent Neural Network

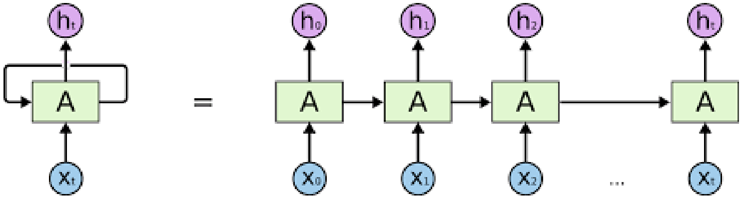


- **Objective:** modeling temporal structure



- **Objective:** modeling temporal structure
- **General idea:** the network maintains a hidden state h_t called *memory*

Recurrent Neural Network



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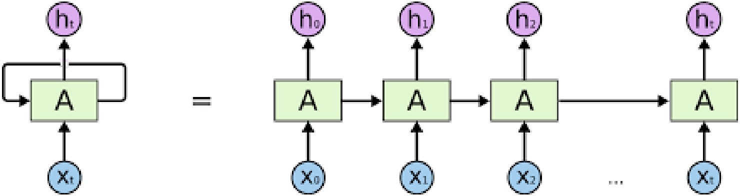

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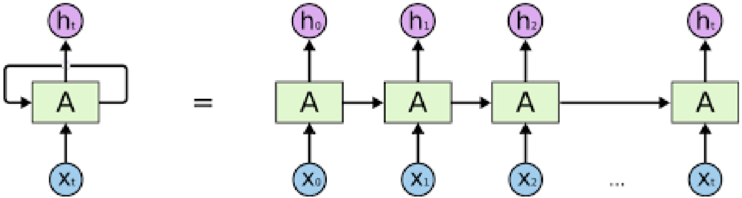

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- **General idea:** the network maintains a hidden state h_t called *memory*
- **Update:** $h_{t+1} = f(h_t, x_t)$
- There exists many type of RNNs: LSTMs, GRUs, etc...
- Can also be used to model spatial structure.
- Successful for sequence learning in natural language processing, speech recognition, etc.

Deep Learning In Practice

- Tensorflow, Pytorch: high level python-based language doing all the tedious work.

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return softmax(Relu(layer2(Relu(layer1(test_set)))))
```

Presentation Layout

In the next hour, we will get insight on:

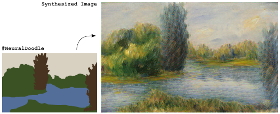
- Motivation for Deep Learning on Raster Imagery
- Semantic Segmentation Fully-conv. Networks
- Multi-modal Classification
- Object Detection
- Change Detection and Multi-temporal Analysis
- Classif. of Hyperspectral Data
- Deep Learning on SAR Data
- Resources
- Practical Session: Semantic Segmentation
- Bibliography 2D

Lots of common application in everyone's life:

Self-driving cars

Facebook's facial recognition

Google Translate... images



Painting like Monet!

Figure: Applications of Deep Learning

So... what can we do in remote sensing?

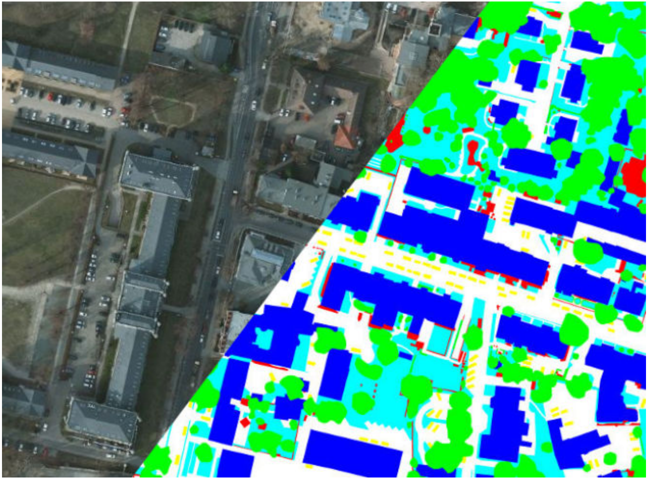


Figure: Can we understand and translate images to cartography?

Motivation for Deep Learning on Raster Imagery

Data Evolution	*Feature Extraction*	*Classification*
resol. −	Pixel-based filtering	Manual modeling, thresholding
resol. +	Textures, local features	Distribution estimates (GMMs, etc.)
data +		Learning-based classifiers (SVMs, ensemble methods: random forests, boosting): high-dimensional, non-linear, complex
resol. ++	Complex features (object modeling)	active learning, latentSVM
data ++	Patchs of pixels, filter banks	Deep neural networks (RBM, RCNN)

resolution, quantity

Figure: An history of classification in remote sensing

Motivation for Deep Learning on Raster Imagery

- In some specific cases, standard machine learning approaches or sensor-based heuristics are well enough...
- but Convolutional Neural Networks make good **generic classifiers**

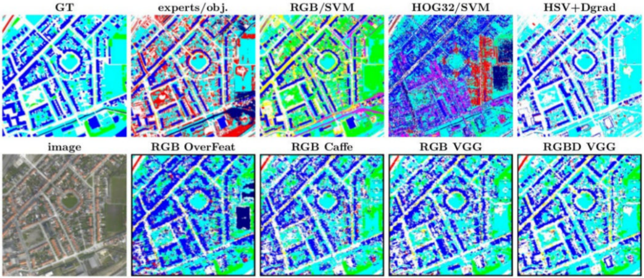


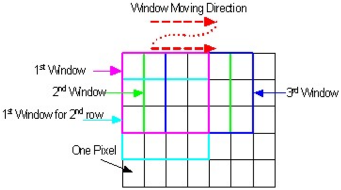
Figure: Benchmarking old-school vs. deep learning methods (Campos-Taberner et al., 2016)

Simple Deep Learning Baseline

3D	*Algorithm*	Imp. surf.	Build.	Low veg.	Tree	Car	Clutter	Boat	Water	Overall acc. %	Cohen κ
★	Expert	58.97	63.87	74.55					92.39	∅	∅
	RGB/SVM	53.89	53.53	50.32	32.97	24.02	13.75	12.12	98.52	60.77	0.52
★	RGB*d*/SVM	14.51	67.79	38.03	27.43	7.15	1.12	14.58	98.45	50.76	0.41
★	RGB*d*I/SVM	60.86	69.01	57.12	38.12	11.59	20.49	15.04	94.42	63.83	0.56
	HOG32/SVM	28.94	43.17	48.77	27.32	30.24	17.39	12.61	88.02	52.45	0.41
	HOG16/SVM	39.52	38.45	35.65	29.99	21.93	16.13	13.52	80.02	49.4	0.36
	HSV/SVM	71.60	46.97	68.38	0.12	0.00	13.71	0.00	92.14	70.16	0.60
★	HSVDGr/SVM	73.30	70.85	68.75	0.17	0.00	17.11	0.00	92.37	73.60	0.65
	SOM							51.45		∅	∅
	DtMM					48.46				∅	∅
	RGB OverFeat/SVM	55.86	63.34	59.48	64.44	36.03	28.31	41.51	92.07	67.97	0.59
	RGB Caffe/SVM	62.32	62.66	63.23	60.84	31.34	32.49	46.57	95.61	71.06	0.63
	RGB VGG/SVM	63.18	64.66	63.60	66.98	31.46	43.68	51.92	95.93	72.36	0.64
★	RGB*d* VGG/SVM	66.02	74.26	65.04	66.94	32.04	44.96	50.61	96.31	74.77	0.67
★	RGBd^+ VGG/SVM	67.66	72.70	68.38	78.77	33.92	45.6	56.10	96.50	76.56	0.70
★	RGBd^+ trained AlexNet	79.10	75.60	78.00	79.50	50.80	63.40	44.80	98.20	83.32	0.78

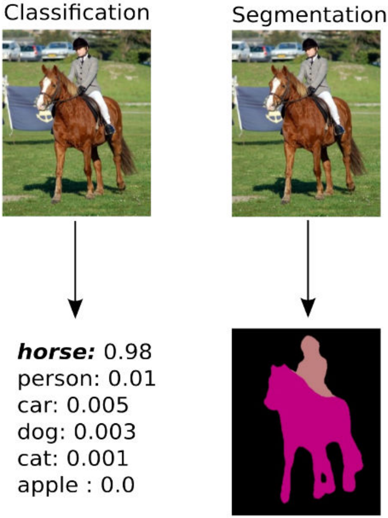
Figure: Benchmarking old-school vs. deep learning methods (Campos-Taberner et al., 2016)

Remote Sensing processing:

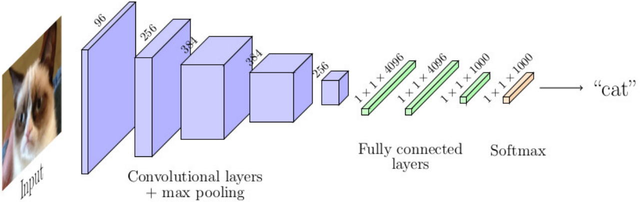


- Extract patches from the image using a sliding window with overlap
- Train on images with ground-truth
- Apply on test patches (average several predictions on overlapping pixels)

- **Classification:** 1 image (or local patch in remote sensing) $\longrightarrow$ 1 label
- **Segmentation:** 1 pixel $\longrightarrow$ 1 label
- Image = structured pixel ensemble



AlexNet CNN for classification (Krizhevsky et al., 2012)



Fully-convolutional AlexNet for semantic segmentation (Long et al., 2015)

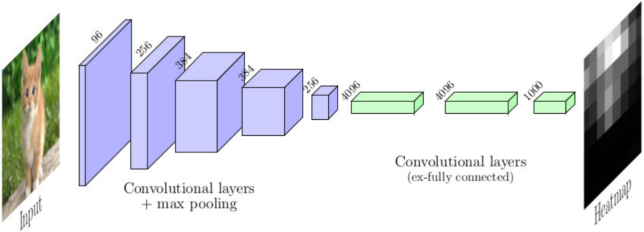
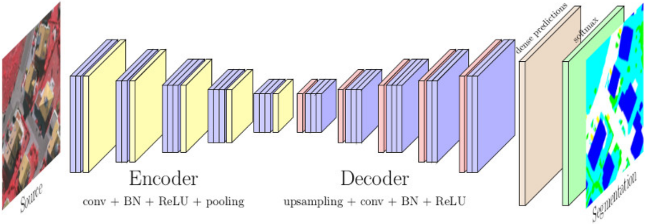
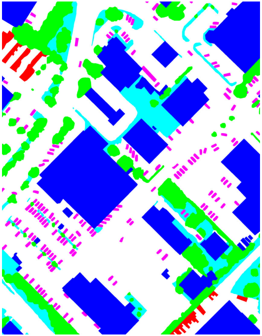


Figure: Fully-convolutional networks (FCNs)

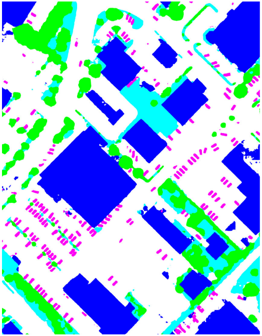


- SegNet: A deep convolutional Encoder-Decoder architecture for Image Segmentation (Bandrinarayanan et al., 2016)
- And today: U-Net (Ronneberger et al., 2015), Hourglass (Newell et al. 2016))

IR/R/G 10cm/pixel



Ground-truth



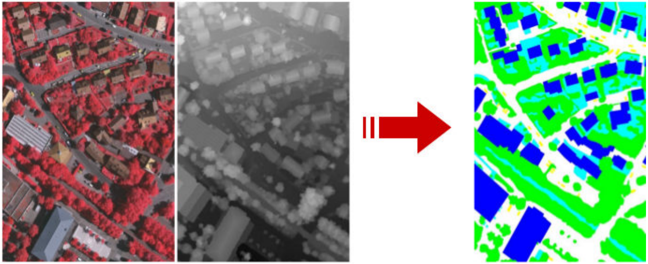
SegNet

Figure: SegNet semantic segmentation (Audebert et al., 2017a)

Multi-modal Semantic Segmentation

How to automatically generate maps from aerial imagery?

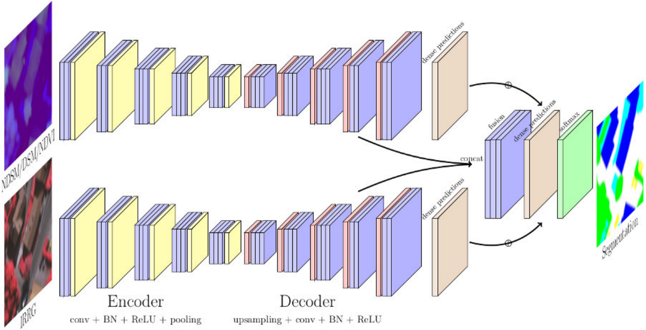
- Non-standard (yet complimentary) imagery: multispectral, LiDAR...
- Auxiliary data: existing open-source maps (OpenStreetMap, etc.)

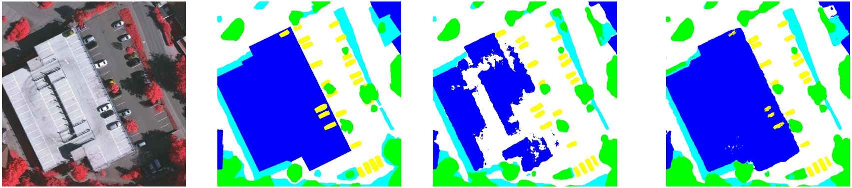


Multi-modal Semantic Segmentation

How to automatically generate maps from aerial imagery?

- Dual-stream networks which translate data to representations (coding)...
- Fusion and decoding from representations to maps





IR/R/G | Ground-truth | IR/R/G pred. | IR/R/G +DSM pred.

Figure: Multimodal semantic segmentation results (Audebert et al., 2017a)

- Sensor-based information helps!

Multi-modal Semantic Segmentation

How to automatically generate maps from aerial imagery using auxiliary maps?

- Incorporate information to guide the process, FuseNet: (Hazirbas et al., 2016)
- Faster training and better results!

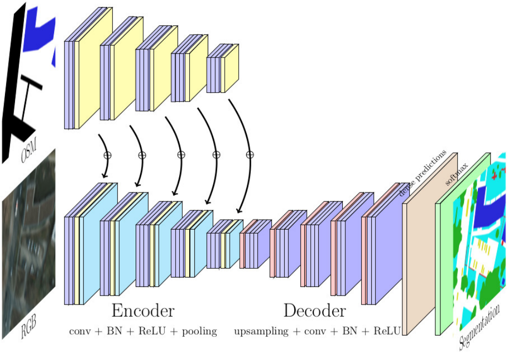


Figure: Joint learning of RGB imagery and OSM (Audebert et al., 2017b)

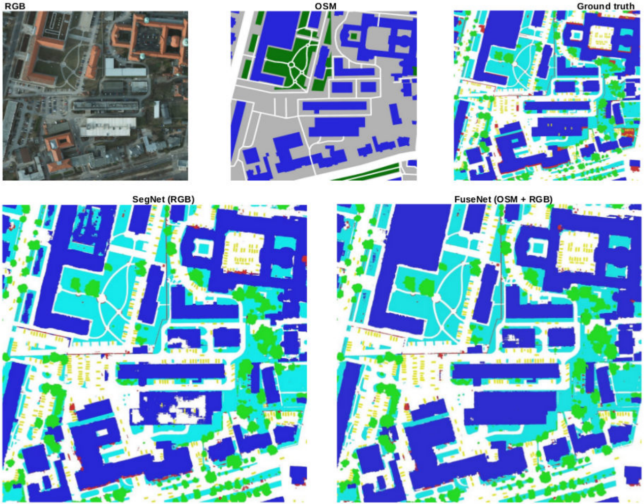
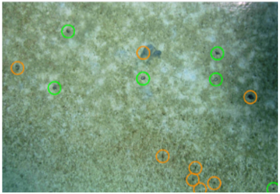


Figure: RGB+OSM semantic segmentation results (Audebert et al., 2017b)

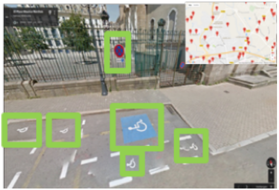
Object Detection

Any generic detection network (e.g. Faster-RCNN) can be fine-tuned to fit user's needs, e.g.:

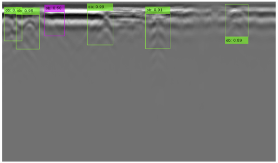
- mapping and monitoring marine turtles from UAVs in environmental surveys
- detecting accessibility signs to map related parking lots
- detect and map buried networks from geophysical data (ground-penetrating radar)



Turtle detection
WIPSEA



Accessibility mapping
(Nassar & Lefèvre, 2019)



Buried network detection
(Pham & Lefèvre, 2018)

How to extend semantic analysis to multi-temporal data ?

- detect changes
- monitor activity in high-revisit rate acquisitions
- focus on specific changes (urban, agriculture, vehicles, industrial activity...)

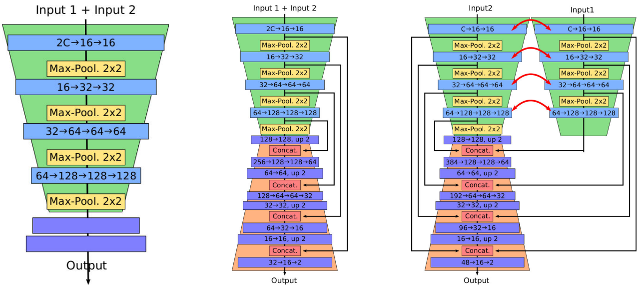
Date 1

Date 2

Change map

How to extend semantic analysis to multitemporal data ?

- As before, simply concatenating images...
- Or with siamese networks, i.e. dual stream nets which share weights.



Standard CNN U-Net Siamese network

Figure: CNN / FCN architectures for change detection. (Daudt et al., 2018)

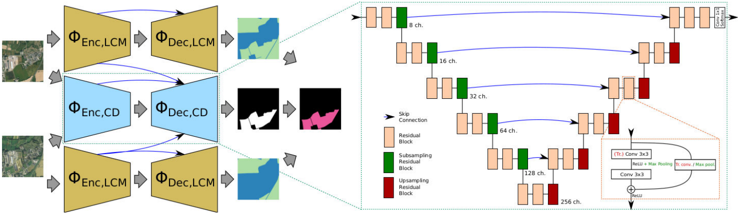
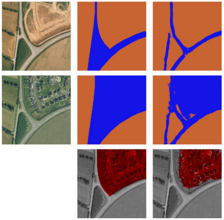


Figure: Semantic change detection. (Daudt et al., 2019)

Semantic change detection:

- Joint multi-task learning of semantics and differences with FCNs
- Prediction of land cover and change maps



Siamese networks can work with very different inputs! (e.g. ground vs aerial imagery)

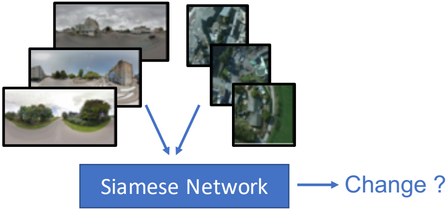


Figure: Multiview change detection (Lefèvre et al. 2017)

Recurrent Neural Networks

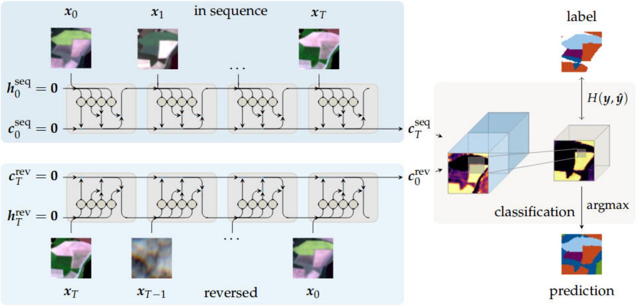


Figure: Multi-Temporal Land Cover Classification with Recurrent Auto-encoders (Russwurm & Köner, 2018)

Classification of Hyperspectral Data

How to extend semantic analysis to hyperspectral imaging (HSI) data ?

- RGB to 100+ bands, image to data cube;
- finer spectral description, out-of-visible;
- lower resolution but finer class discrimination (materials, stressed or healthy vegetation...)

Figure: Hyperspectral data cube: Houston (Texas, USA) – IEEE GRSS IADF TC's Data Fusion Contest 2018

CNN architectures adapted to HSI classification:

- 1D CNN: spectrum classification
- 1D RNN: spectral sequence classification

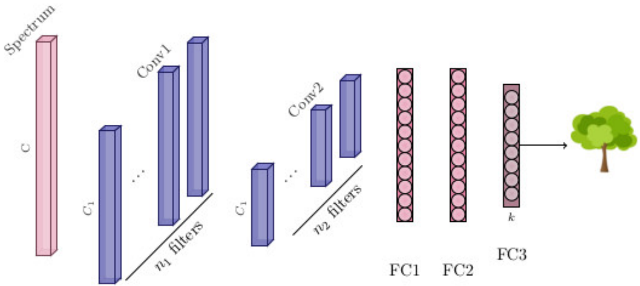


Figure: CNN 1D

CNN architectures adapted to HSI classification:

- Spatial-spectral, 2D+1D approaches
- Reduce to RGB-like data + 2D CNN
- PCA or supervised reduction : alternate 2D and 1D convolutions

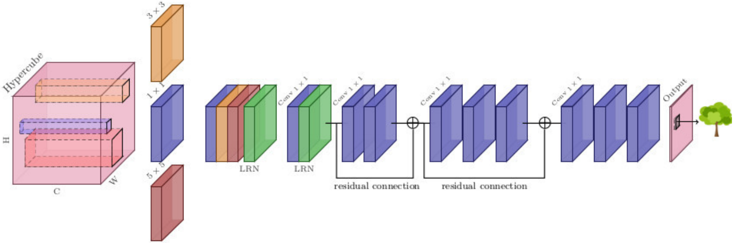


Figure: CNN 2D+1D (Lee et al., 2016)

CNN architectures adapted to HSI classification:

- End-to-end 3D pattern recognition: apply learnable (w, h, B) filters on the hypercube

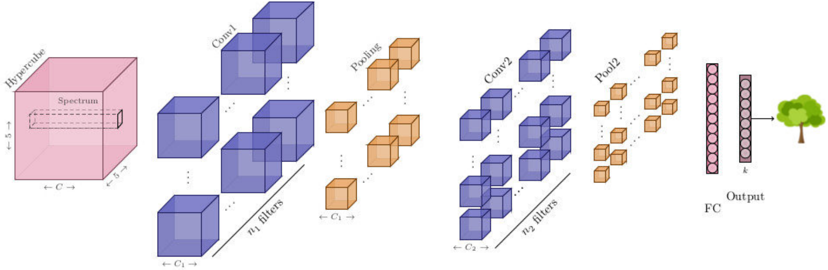


Figure: CNN 3D (Audebert et al, 2019)

HSI classification with CNNs:

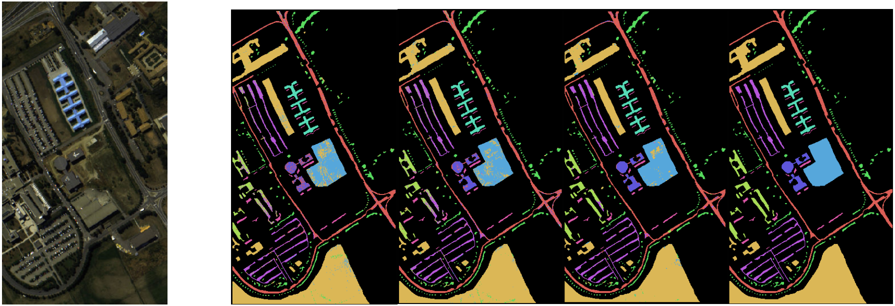


Figure: Comparison of HSI classifications with various CNNs (Audebert et al, 2019)

Deep learning on SAR Data

How to extend deep learning processing to SAR data ?

- Specific physics, different from optical images: intensity + phase;
- High resolution, "cloud-free" images;
- Presence of "speckle" and changing appearance depending on the angle of view.

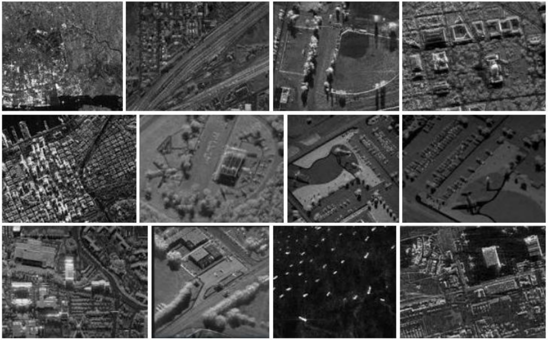


Figure: SAR image examples

Despeckling:

- Inspired by denoising Denoising Auto-Encoders (Vincent et al., 2010);
- Auto-encoder learn to reconstruct the image from itself
- Denoising / despeckling autoencoders learn to reconstruct the image from the image with added speckle

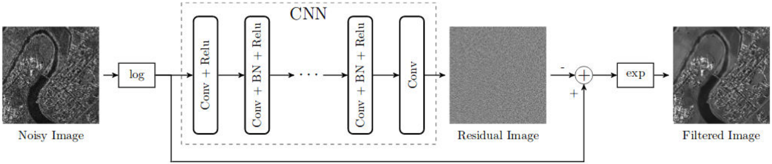
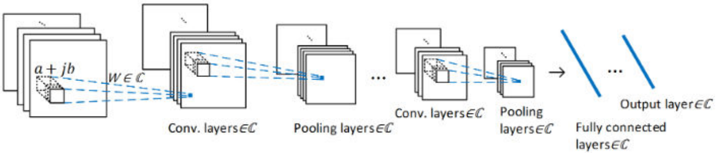


Figure: Despeckling auto-encoder (Chierchia et al., 2017)

Classification of SAR Data

- Usually straightforward (but do they miss something?);
- Complex valued CNN for processing intensity + phase images (Haensch & Hellwich, 2010) (Zhang et al., 2010)



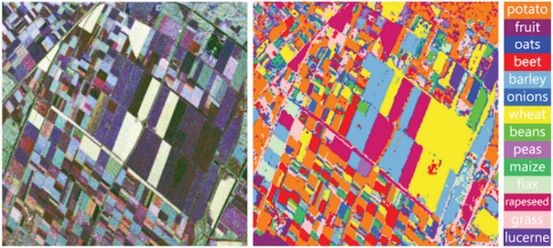


Figure: SAR classification (Zhang et al., 2017) and (Zhu et al., 2017)

Similarly to optical imagery, SAR imagery can be exploited in many ways, e.g.

- ship analysis from Sentinel-1: detection, length estimation, classification

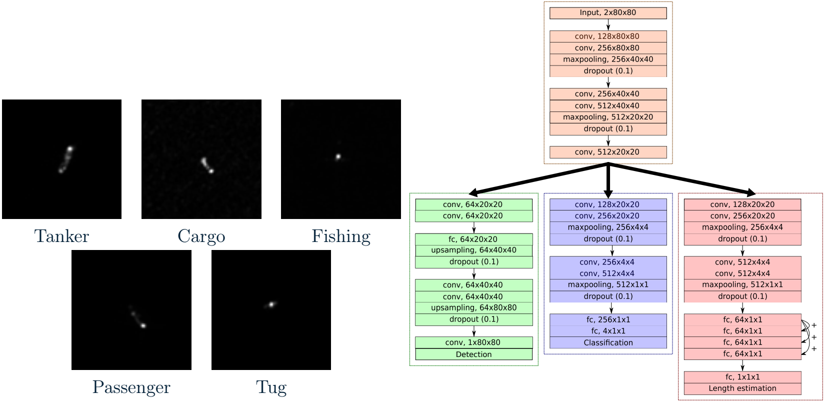


Figure: Dechesne et al., 2019

Public resources

Good reads:

- **Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art**, *Zhang, Zhang and Du*, IEEE Geosci. and Rem. Sens. Mag, 6 (2) June 2016
- **Deep learning in remote sensing: A comprehensive review and list of resources**, *Zhu, Tuia, Mou, Xia, Zhang, Xu, and Fraundorfer*, IEEE Geosci. and Rem. Sens. Mag, 5 (4) Dec. 2017
- **Deep Learning for Classification of Hyperspectral Data: A Comparative Review**, *Audebert, Le Saux and Lefèvre*, IEEE Geosci. and Rem. Sens. Mag., 7 (2) June 2019

Public resources

Toolbox:

- DeepNetsForEO (`https://github.com/nshaud/DeepNetsForEO`): python code for semantic segmentation of aerial / satellite imagery
- DeepHyperX (`https://github.com/nshaud/DeepHyperX`): python toolbox for classification of hyperspectral imagery (spectral, spatial-spectral and 3D convolutions)

Public resources

Public datasets:

- ISPRS datasets: semantic labeling, reconstruction $\rightsquigarrow$ https://www.isprs.org/data/
- IEEE GRSS Data Fusion Contests: http://www.grss-ieee.org/community/technical-committees/data-fusion/data-fusion-contest/
- IEEE GRSS: hyperspectral datasets with standard train/test splits (DFC2018, Pavia, Indian Pines) $\rightsquigarrow$ http://dase.grss-ieee.org/
- INRIA Aerial Semantic labeling dataset: buildings $\rightsquigarrow$ https://project.inria.fr/aerialimagelabeling/
- XView: objects in aerial images $\rightsquigarrow$ http://xviewdataset.org/
- DOTA: Detecting Objects in Aerial images $\rightsquigarrow$ https://captain-whu.github.io/DOTA/dataset.html

Practical session: objectives

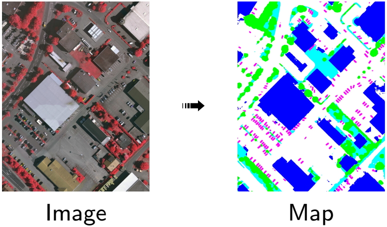
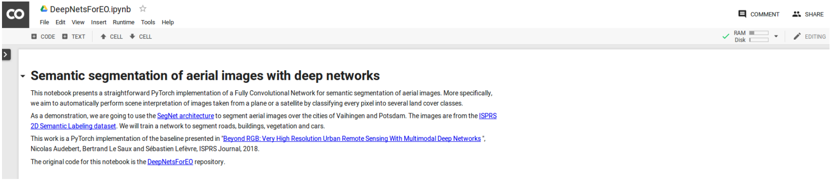


Figure: Let's practice: semantic segmentation of Earth-observation data!

We will:

- load data and perform data augmentation;
- define a network model
- train the network on colab's GPU
- test the net on some test images and evaluate results



Link (in 2 clicks): https://blesaux.github.io/teaching/DL4RS

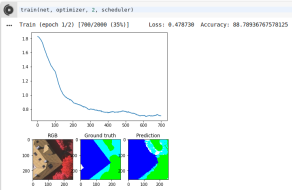


Figure: That's a good start!

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Presentation Layout

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Capturing a 3D world

- 3D data crucial for robotics, autonomous vehicle, 3D scale models, virtual reality etc...

credit: medium, VisionSystemDesign, microsoft

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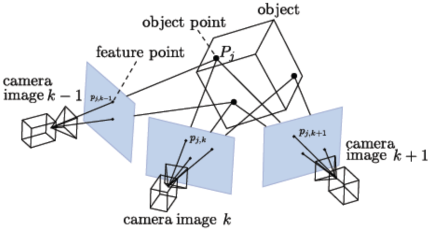
- Can be computed from images: stereo, SfM, SLAM (cheap, not precise).



credit: computervisionblog, velodynelidar

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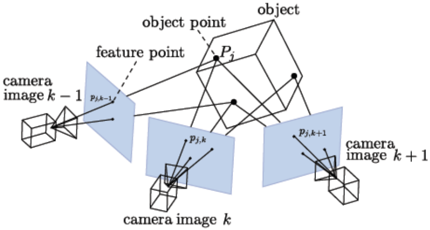
- LiDAR (expensive, precise).



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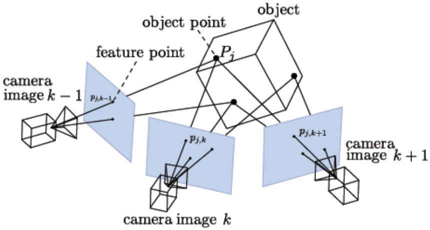

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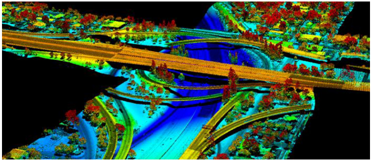

credit: clearpath robotics, tuck mapping solutions

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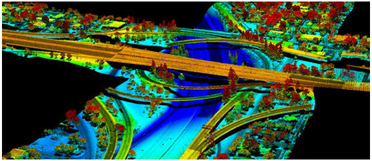

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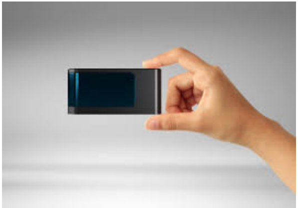
Future trends

- LiDAR are getting cheaper :$100k\$ \rightarrow 2k\$$ in a few years.



credit: velodynelidar, green car congress

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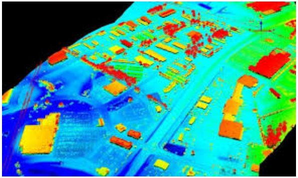

credit: velodynelidar, spar3d

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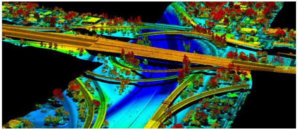

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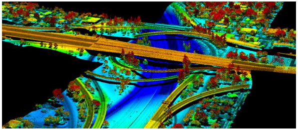

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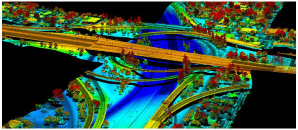
- Rapid progress in harware and methodology + major applications = **a booming field.**



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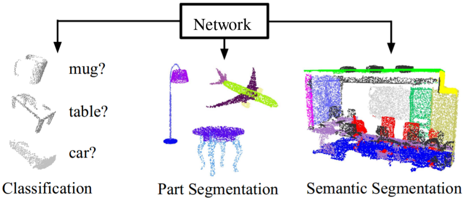
$$P \mapsto \mathcal{K}$$



credit: Qi et. al. 2017a

Analysis of 3D point clouds

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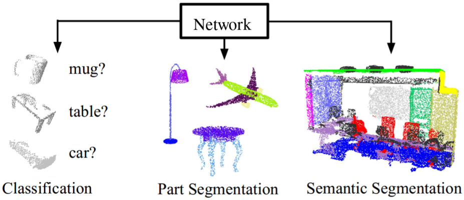

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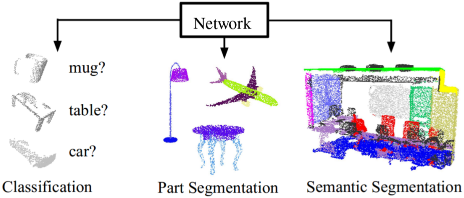

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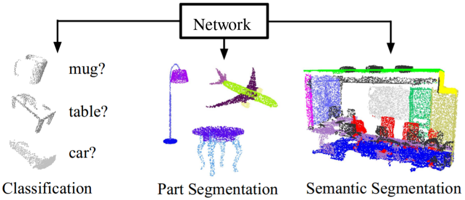
- **Instance Segmentation**: cluster the point cloud into semantically characterized objects:

$$P_i \mapsto [1, \cdots, C]$$
$$[1, \cdots, C] \mapsto [1, \cdots, K]$$



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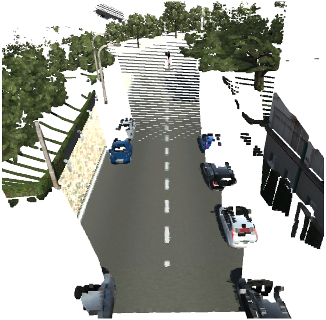
What makes 3D analysis so hard



- Data volume considerable.

credit: Gaidon2016, Engelmann2017, Hackel2017

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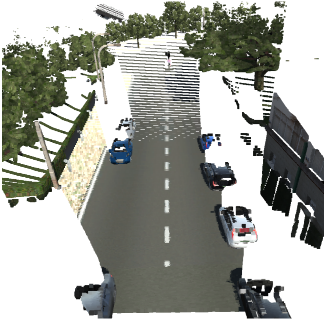

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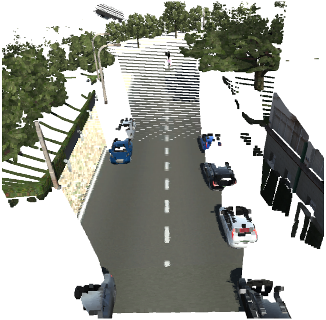

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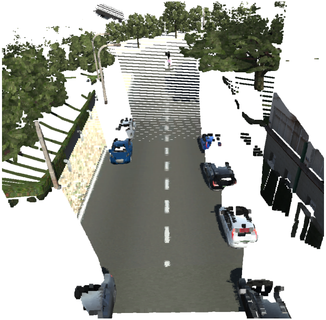

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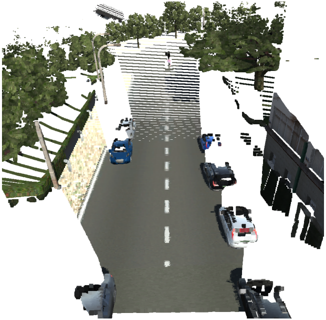
credit: Gaidon2016, Engelmann2017, Hackel2017

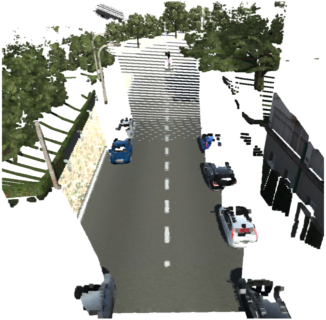
What makes 3D analysis so hard

- Data volume considerable.
- Lack of grid-structure.
- Permutation-invariance.
- Sparsity.
- Highly variable density.



credit: Gaidon2016, Engelmann2017, Hackel2017

What makes 3D analysis so hard



- Data volume considerable.
- Lack of grid-structure.
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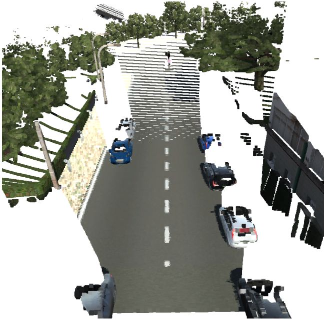

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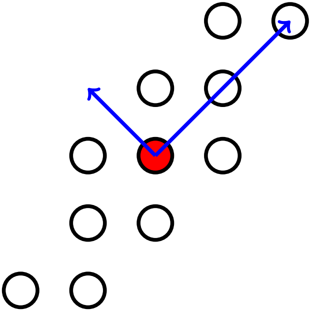
Presentation Layout

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

Demantke2011



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

$$\text{Pla} = \frac{\sqrt{\lambda_2} - \sqrt{\lambda_3}}{\sqrt{\lambda_1}}$$

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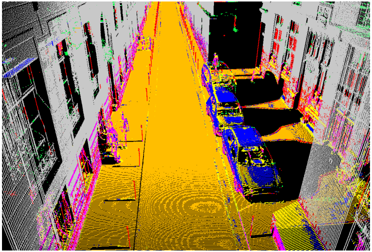
Pointwise classification



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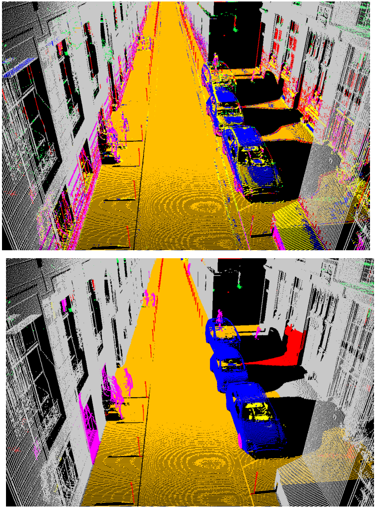
credit: landrieu et. al. 2017a



- **Step 1:** compute point features based on neighborhood
- **Step 2:** classification (RF, SVM, etc...)
- **Step 3:** smoothing to increase spatial regularity (with CRFs, MRFs, graph-structured optimization, etc...)

Demantke2011
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Presentation Layout

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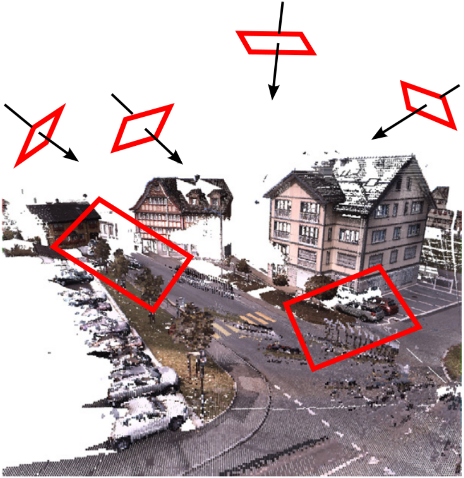

Boulch et. al. 2017

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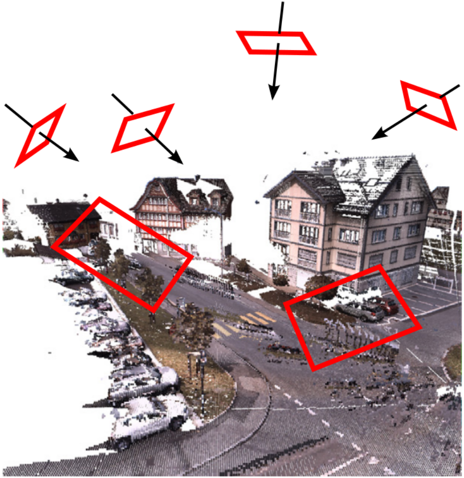

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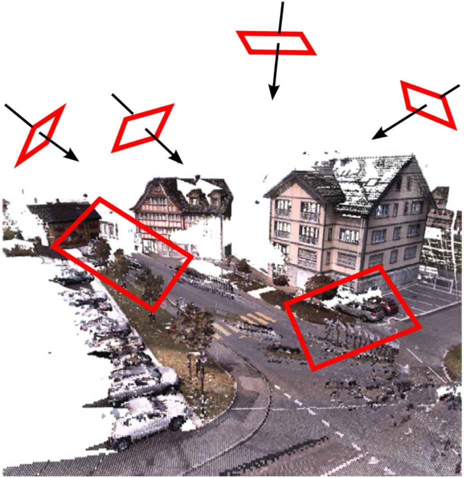
Boulch et. al. 2017



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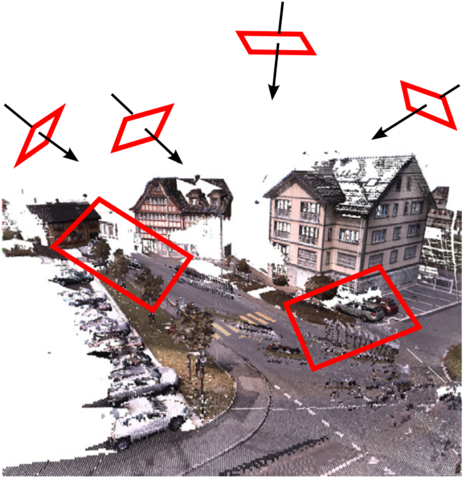

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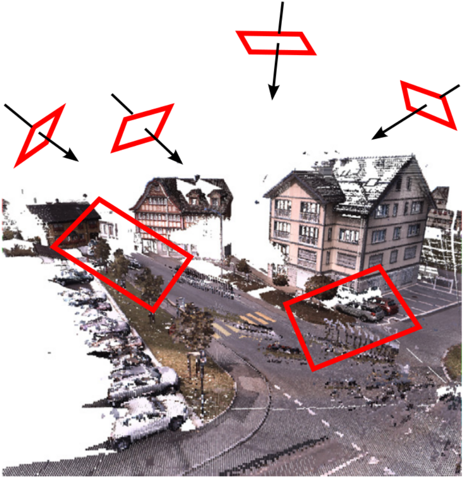
Boulch et. al. 2017



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Voxel-Based Methods

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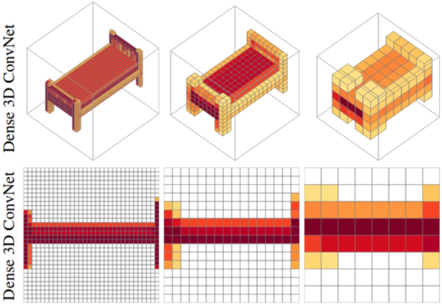

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credit: Riegler2017, Tchapmi2017, Jampani2017

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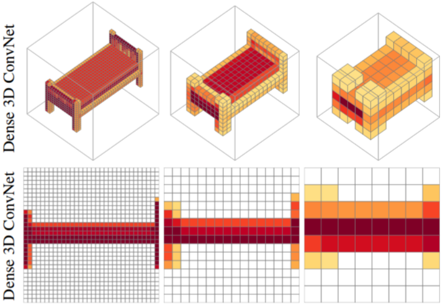

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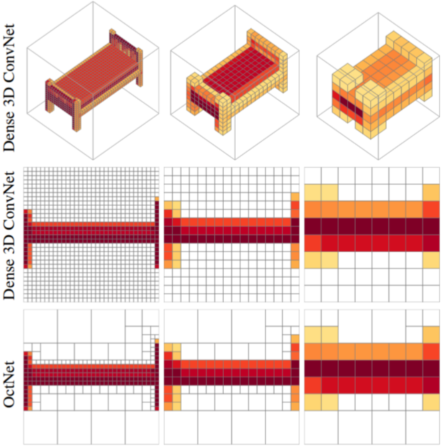

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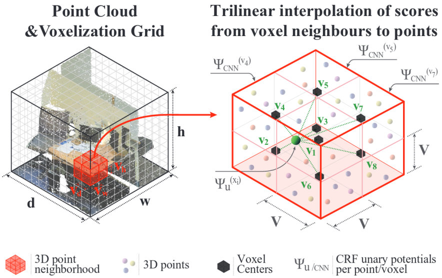

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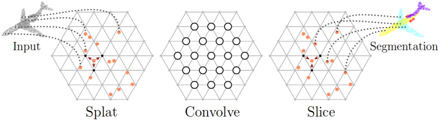
- **Idea 3:** SplatNet, sparse convolutions with hashmaps.



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3D Convolution-Based Methods

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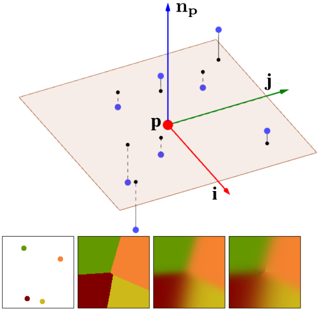

Tatarchenko2018

credit: Tatarchenko2018, Li2018

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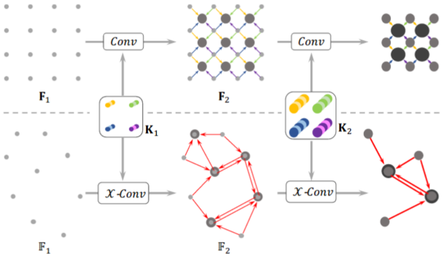

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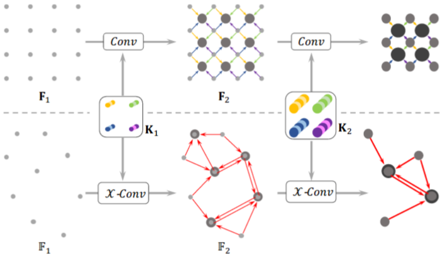

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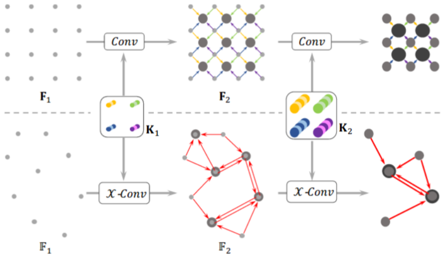
- The invariance is learnt!



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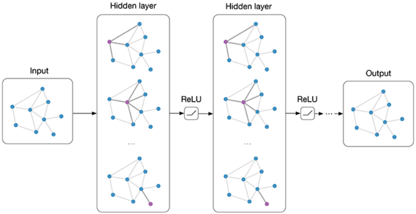
Graph-Neural Network

- Generalize convolutions to the general graph setting.



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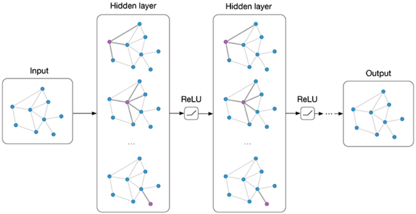

Qi2017, Simonovski2017

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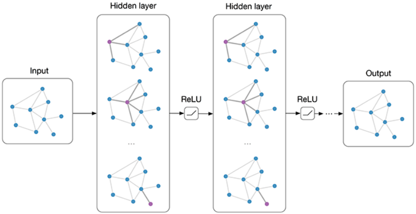

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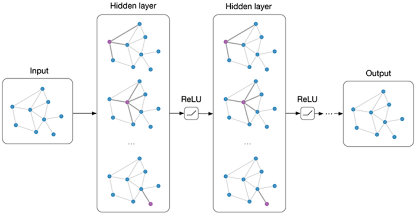
$$h_i^{(t+1)} = g(\sum_{j \to i} f(h_i^t), h_i^t)$$



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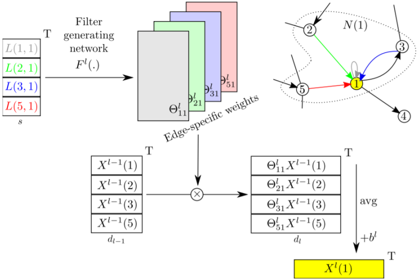
- ECC **Simonovski2017** messages are conditioned by edge features:

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



Qi2017, Simonovski2017

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Presentation Layout

- A cornerstone of modern 3D analysis

Qi et. al.2017a

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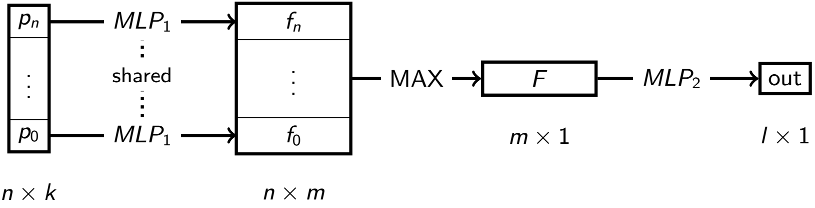
- **A fondamental constraint:** inputs are invariant by permutation

Qi et. al.2017a

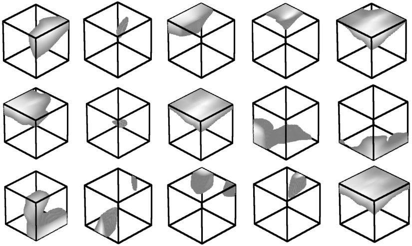
- A cornerstone of modern 3D analysis
- **A fondamental constraint:** inputs are invariant by permutation
- **Solution:** process points independently, apply permutation-invariant pooling, process this feature with a MLP.
- Computes a global shape descriptor.
- n: number of points, k size of observations, $e^{(i)}$ size of intermediary embeddings, $e^{(f)}$ size of output



Qi et. al.2017a

PointNet II

- **Point function**: activate at different parts of the unit cube, learned spatial features.



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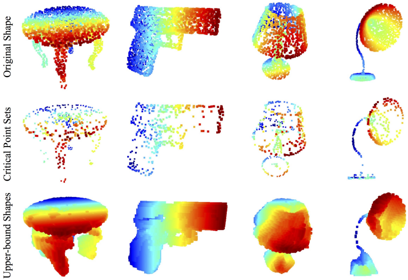

PointNet II

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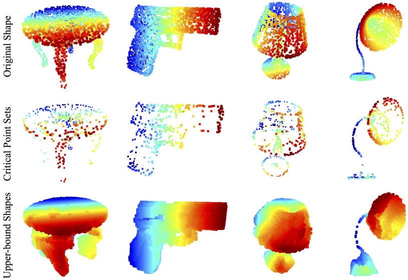
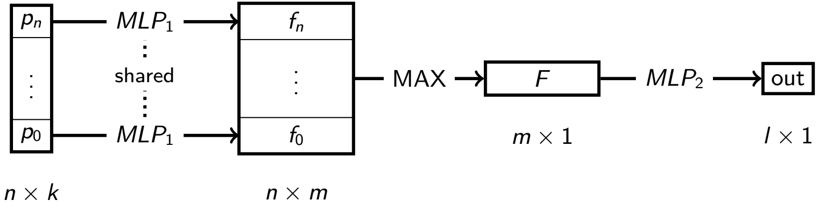
- **Upper Bound Shape**: maximal point cloud with exactly the same global embedding



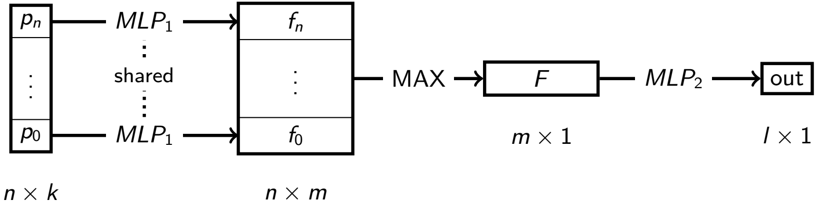
PointNet for Cloud embedding

- `point_input`$_i$: point features (coordinate, color, etc...)



Qi et. al.2017a

- point_input$_i$: point features (coordinate, color, etc...)
- point_embedding$_i$ = MLP_1(point_input$_i$)



Qi et. al.2017a

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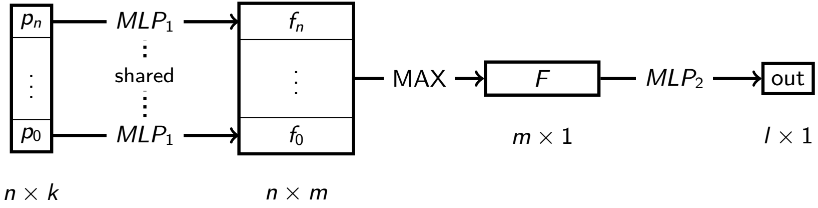

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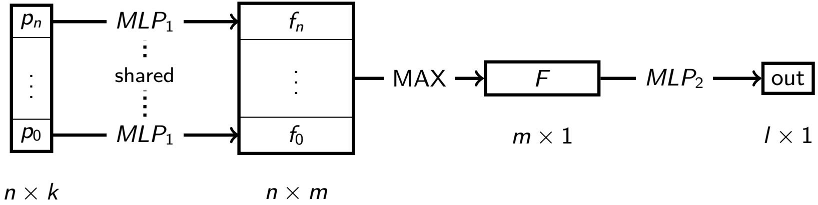

Qi et. al.2017a

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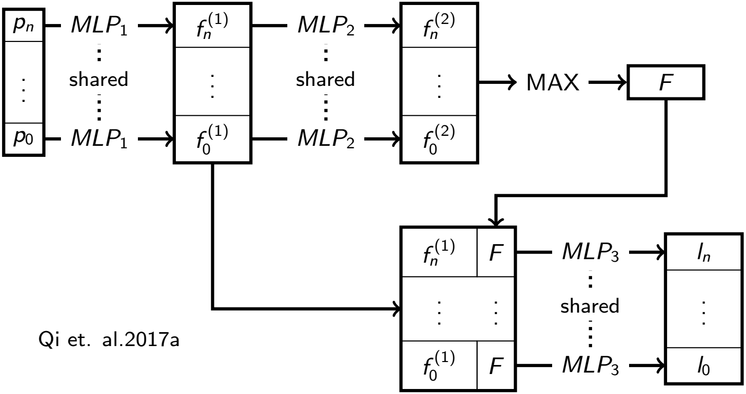

Qi et. al.2017a

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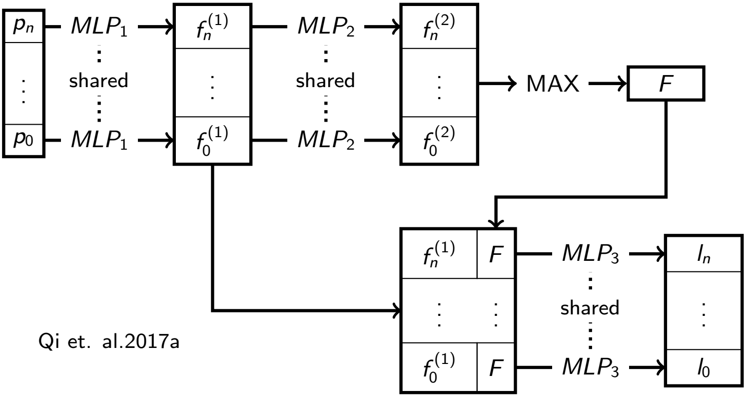

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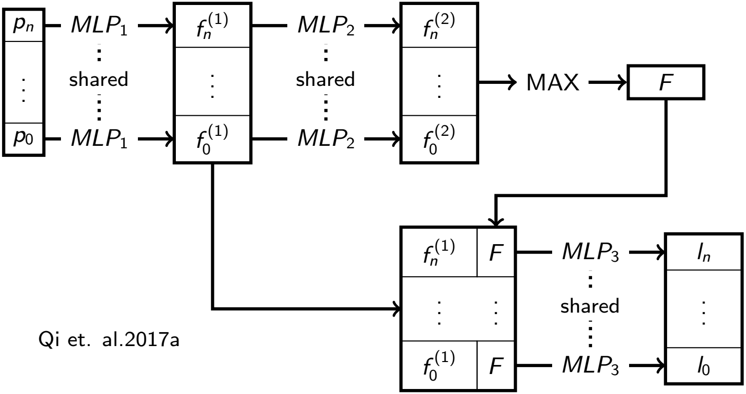

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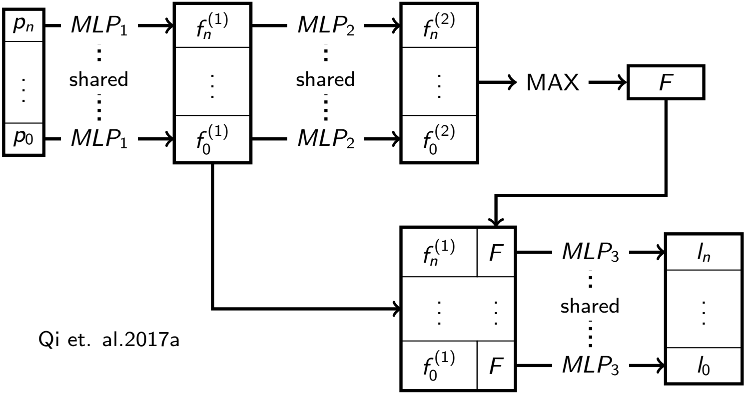

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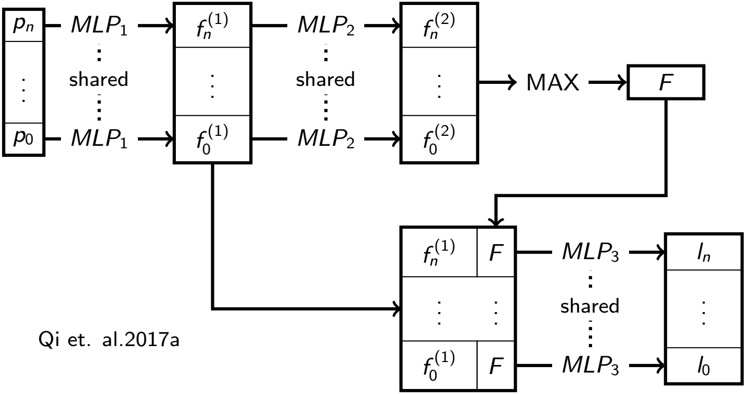
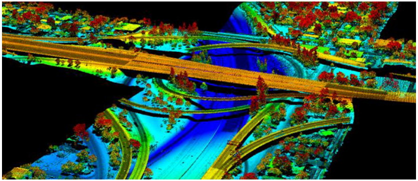


Qi et. al.2017a

Presentation Layout

Why we need to scale

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



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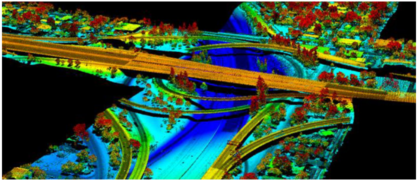

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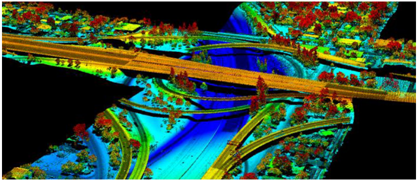

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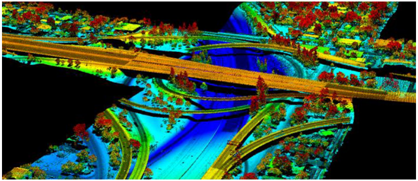
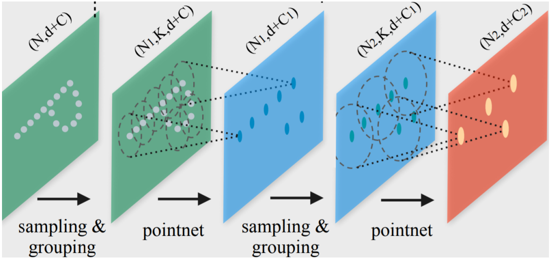
  - **Sliding windows**: loses the global structure.



credit: tuck mapping solution

PointNet++

- Pyramid structure for multi-scale feature extraction.

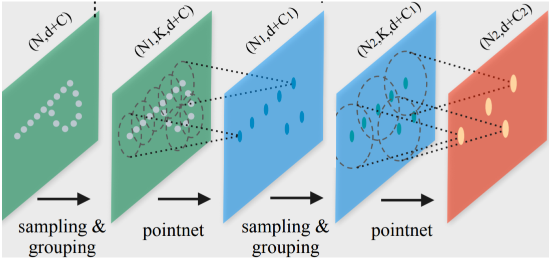


Qi et. al.2017b

credit: Qi et. al.2017b

PointNet++

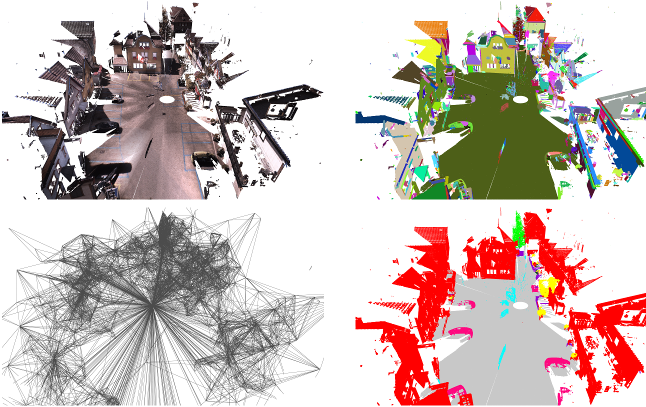
- Pyramid structure for multi-scale feature extraction.
- From local to global with with increasingly abstract features.



Qi et. al.2017b

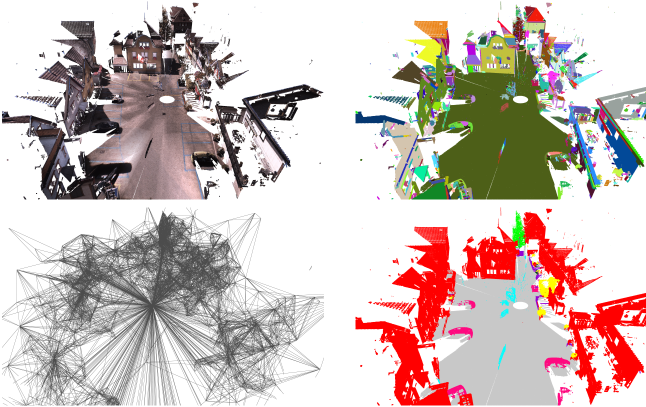
credit: Qi et. al.2017b

- **Observation:**
  $n_{\text{points}} \gg n_{\text{objects}}$.



Landrieu&Simonovski2018

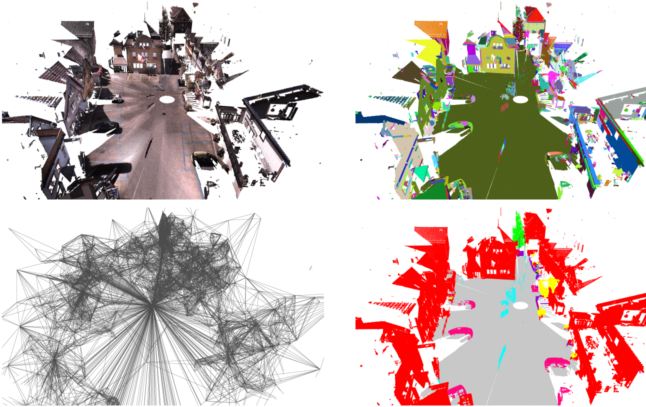
- **Observation:** $n_{\text{points}} \gg n_{\text{objects}}$.
- Partition scene into superpoints with simple shapes.



Landrieu&Simonovski2018

SuperPoint-Graph

- **Observation:**
  $n_{\text{points}} \gg n_{\text{objects}}$.
- Partition scene into superpoints with simple shapes.
- Only a few superpoints, context leveraging with powerful graph methods.

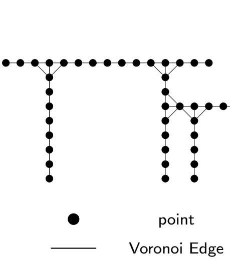


Landrieu&Simonovski2018

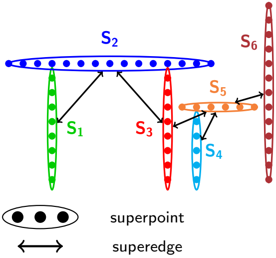
Pipeline

Step	Complexity	Algorithm
Geometric Partition into simple shapes	very high 10^8 points	ℓ_0-cut pursuit
Superpoint embedding learning shape descriptors	low subsampling to 128 points	PointNet
Contextual Segmentation leveraging the global structure	very low $\sim$ 1000 vertices	ECC with GRUs

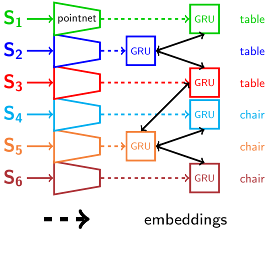
Pipeline



(a) Point cloud



(b) Superpoint graph



(c) Convolution Network

Presentation Layout

Main Annotated Academic Datasets

- **Semantic3D**: outdoor, fixed LiDAR, 4×10^9 points

credit: Armeni2016, Gaidon2016, Engelmann2017, Hackel2017

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- **Semantic3D**: outdoor, fixed LiDAR, 4×10^9 points
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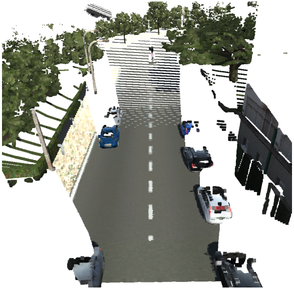
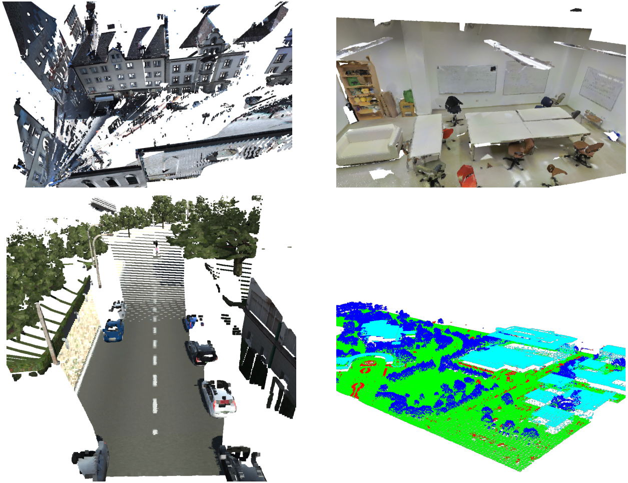
- **vKITTI**: embarked, virtual LiDAR, 2×10^8 points.



credit: Armeni2016, Gaidon2016, Engelmann2017, Hackel2017

- **Semantic3D**: outdoor, fixed LiDAR, 4×10^9 points
- **S3DIS**: indoor, fixed LiDAR, 6×10^8 points
- **vKITTI**: embarked, virtual LiDAR, 2×10^8 points.
- **GRSS**: aerial LiDAR, $\sim 10^7$ points.



credit: Armeni2016, Gaidon2016, Engelmann2017, Hackel2017

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- New contenders weekly: PointSIFT, etc...
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- Start with a simple PointNet + sliding window baseline
- Move on to PointCNN/PointSIFT if precision is an issue
- Move on to SPG for scaling/global structure.

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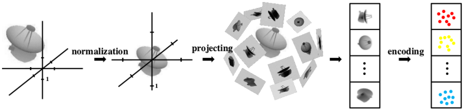
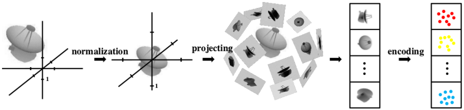
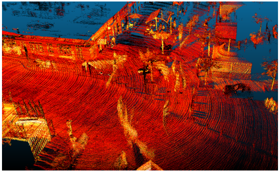
- **Which algorithm to chose in practice:**
  - Start with a simple PointNet + sliding window baseline
  - Move on to PointCNN/PointSIFT if precision is an issue
  - Move on to SPG for scaling/global structure.
- Pay attention near big conferences (CVPR, ICCV), new models released constantly.

Future of the Field

- Efficient auto-encoders for semi-supervized learning **Zhu2016**

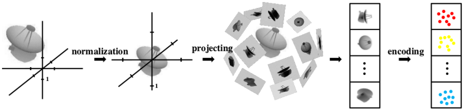


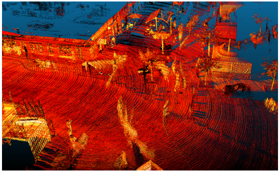


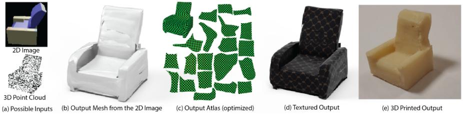


- Efficient auto-encoders for semi-supervized learning **Zhu2016**
- Real-time analysis for dynamic 3D data for autonomous driving

- Efficient auto-encoders for semi-supervized learning **Zhu2016**
- Real-time analysis for dynamic 3D data for autonomous driving
- Deep learning for other remote sensing tasks: segmentation, object detection, surface reconstruction. **Groueix2018**







Presentation Layout

1. Presentation of Speakers
2. Deep Learning Basics
3. Deep Learning on Raster Imagery
4. Deep Learning on 3D Point Clouds
   - Presentation of the Problem
   - Traditional Approaches
   - First Deep-Learning Approaches
   - PointNet - set-based approach
   - Scaling Segmentation
   - In Practice
   - Bibliography

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Public resources

Today:

- Neural Net Basics
- Deep Learning in 2D Remote Sensing
- Deep Learning in 3D Remote Sensing

Thanks for you attention!

Comments and questions after the course:
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