Graphical Models, Inference and Learning Lecture 8 - Modern Learning / Convolutional Neural Networks

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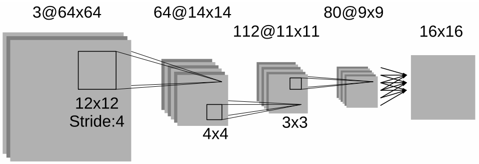
LUXCARTA Technology

Examples of using deep learning for image analysis

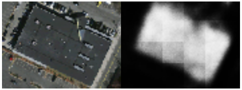
Dense labeling with CNNs in remote sensing

Pioneering works:

1. Predict an entire patch centered in input patch (Mnih, 2013)



- Allows to learn "in-patch location" priors
  $\rightarrow$ Patch border artifacts



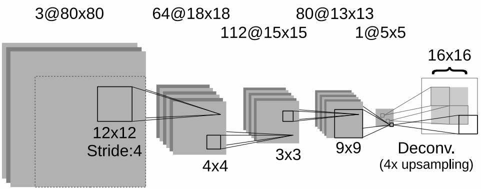
2. Predict the central pixel in the patch and shift one by one
   (e.g., Paisitkriangkrai et al., CVPR Earthvision 2015)
   - Too many redundant computations

Dense labeling with CNNs in remote sensing

Fully convolutional networks (FCNs) [Long et al., CVPR 2015]

- Interpolation with a learned kernel ("deconvolutional" layer)
- Lost resolution is upsampled

Proposed FCN for remote sensing



- Adapted from previous work (Mnih, 2013) and made it fully conv.
- 10x faster and more accurate

E. Maggiori, Y. Tarabalka, G. Charpiat, P. Alliez. "Convolutional neural networks for large-scale remote sensing image classification", IEEE TGRS, 55 (2), 2017.

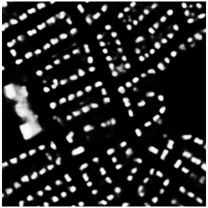
Classification with FCNs: some results

Massachusetts dataset

[Dataset: Mnih, 2013]

Color input

Reference



FCN

Pixelwise SVM

- Classification of 22.5 km^2 (1 m resolution): 8.5 seconds (2.7 GHz 8-core, Quadro K3100M GPU)

E. Maggiori, Y. Tarabalka, G. Charpiat, P. Alliez. "Convolutional neural networks for large-scale remote sensing image classification", IEEE TGRS, 55 (2), 2017.

Yielding high-resolution outputs

Recognition/localization (RL) trade-off

Subsampling:

- increases the receptive field (improving recognition)
- reduces resolution (hampering localization)

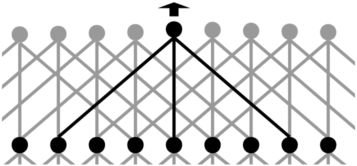
Input Ref. FCN

First architectures for high-resolution labeling

- *Dilation* (Chen et al., 2015; Dubrovina et al., 2016,...)
- *Unpooling/deconv.* (Noh et al., 2015; Volpi and Tuia, 2016,...)
- *Skip networks* (Long et al., 2015; Badrinarayanan et al., 2015,...)

Dilation networks

- Based on the shift-and-stitch approach:
  - Conduct predictions at different offsets to produce low-resolution outputs
  - Interleave these outputs to compose the final high-resolution result
- Such an interleaving can be implemented as convolutions on non-contiguous locations

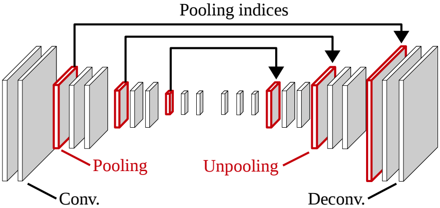


$\Rightarrow$ Larger context without introducing more parameters

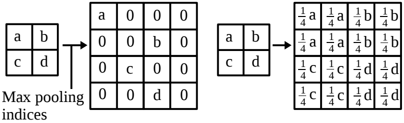
- Not robust to spatial deformation
  (e.g., detect road located *exactly* 5px away)

Unpooling/deconvolution networks

- The CNN is “mirrored” to learn the deconvolution:

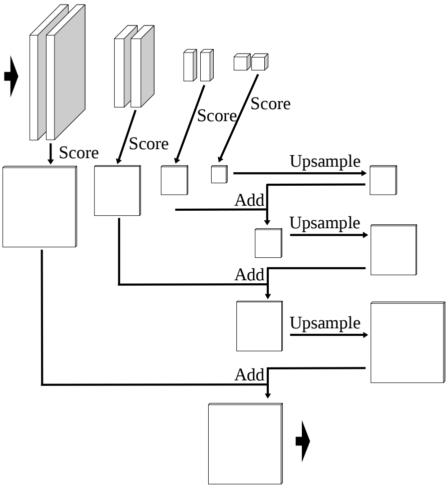


- Max (left) and average (right) unpooling



Skip networks

1. Extract intermediate features
2. Classify
3. Upsample/add (pairwise)



- Addresses trade-off
- Inflexible/arbitrary at combining resolutions

Yielding high-resolution outputs

Premise

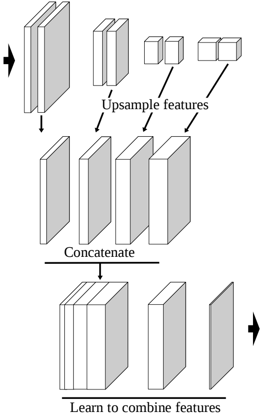
- CNNs do not need to "see" everywhere at the same resolution
- E.g., to classify central pixel:

Full resolution context

Full resolution only near center

$\Rightarrow$ Combine resolutions in a flexible way to address trade-off

To address RL trade-off: MLP network

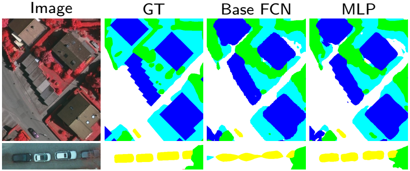


1. Base FCN
2. Extract intermediate features
   ⇒ Pool of features
3. Multi-layer perceptron (1 hidden layer) learns how to combine those features
   ⇒ Pixel by pixel (series of 1×1 convolutional layers)
   ⇒ 128 hidden neurons, nonlinear activation
   ⇒ Output classification map

E. Maggiori, Y. Tarabalka, G. Charpiat, P. Alliez. "High-Resolution Aerial Image Labeling with Convolutional Neural Networks", IEEE TGRS, 55 (12), 2017.

Experiments

Vaihingen & Postdam ISPRS datasets:



Impervious surface (white), Building (blue), Low veget. (cyan), Tree (green), Car (yellow)

Vaihingen	Imp. surf.	Build.	Low veg.	Tree	Car	Acc.
CNN+RF	88.58	94.23	76.58	86.29	67.58	86.52
CNN+RF+CRF	89.10	94.30	77.36	86.25	71.91	86.89
Deconvolution						87.83
Dilation	90.19	94.49	77.69	87.24	76.77	87.70
Dilation + CRF	90.41	94.73	78.25	87.25	75.57	87.90
MLP	**91.69**	**95.24**	**79.44**	**88.12**	**78.42**	**88.92**

Submission to ISPRS server

- Overall accuracy: 89.5%
- **Second place** (out of 29) at the time of submission
- Significantly simpler and faster than other methods

Classifying cities over the earth: can CNNs generalize?

Inria Aerial Image Labeling Dataset (810 km^2, 30 cm resolution, 3 bands):

Bellingham Innsburck San Francisco Tyrol

- Images over US and Austria with open images and building footprints
- Different cities in training and test sets

⇒ project.inria.fr/aerialimagelabeling

E. Maggiori, Y. Tarabalka, G. Charpiat, P. Alliez. "Can Semantic Labeling Methods Generalize to Any City? The Inria Aerial Image Labeling Benchmark". IGARSS 2017.

Inria Aerial Image Labeling Benchmark

- Dec. 2016 - present: $>$ 2000 downloads, $>$ 50 submissions

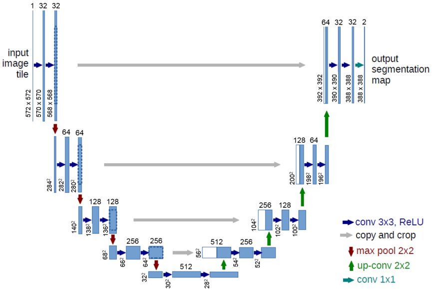
Leaderboard

Method	Date	Bellingham		Bloomington		Innsbruck		San Francisco		East Tyrol		Overall	
		IoU	Acc.	IoU	Acc.	IoU	Acc.	IoU	Acc.	IoU	Acc.	IoU	Acc.
Inria1	3-Jan-17	52.91	95.14	46.08	94.95	58.12	95.16	57.84	86.05	59.03	96.40	55.82	93.54
Inria2	3-Jan-17	56.11	95.37	50.40	95.27	61.03	95.37	61.38	87.00	62.51	96.61	59.31	93.93
TeraDeep	5-May-17	58.08	95.88	53.38	95.61	59.47	95.26	64.34	88.71	62.00	96.57	60.95	94.41
RMIT	16-July-17	57.30	95.97	51.78	95.60	60.70	95.69	66.71	89.23	59.73	96.59	61.73	94.62
Raisa Energy	8-Sep-17	64.46	96.04	56.63	95.38	66.99	95.97	67.74	87.48	69.21	96.92	65.94	94.36
DukeAMLL	6-Nov-17	66.90	96.69	58.48	96.15	69.92	96.37	75.54	91.87	72.34	97.42	70.91	95.70
NUS	13-Nov-17	65.36	96.34	58.50	95.95	68.45	96.21	71.17	90.08	71.58	97.32	68.36	95.18
Onera 1	14-Nov-17	63.42	96.11	62.74	96.20	63.77	95.44	66.53	89.18	65.90	96.76	65.04	94.74
Onera 2	14-Nov-17	68.92	96.94	68.12	97.00	71.87	96.72	71.17	89.74	74.75	97.78	71.02	95.63
NUS	22-Nov-17	70.74	97.00	66.06	96.74	73.17	96.75	73.57	91.19	76.06	97.81	72.45	95.90
DukeAMLL	29-Nov-17	67.14	96.64	65.43	96.73	72.27	96.66	75.72	91.80	74.67	97.70	72.55	95.91
Raisa Energy	30-Nov-17	68.73	96.79	60.83	96.23	70.07	96.31	70.64	89.52	74.76	97.64	69.57	95.30
NUS	11-Dec-17	66.93	96.54	61.42	96.34	71.06	96.47	74.34	91.47	73.21	97.51	70.99	95.67
NUS	15-Dec-17	70.73	97.06	64.87	96.69	73.64	96.86	73.04	91.19	76.36	97.88	72.18	95.94
DukeAMLL	15-Dec-17	68.75	96.89	59.17	96.27	71.82	96.66	69.28	89.90	75.83	97.85	69.15	95.51
Koki Takahashi	22-Dec-17	69.71	96.89	67.10	96.49	78.41	97.47	79.79	93.29	80.15	98.26	76.42	96.48
Tao Hu	2-Jan-18	65.92	96.78	62.05	96.54	72.37	96.91	69.78	90.35	70.21	97.46	68.72	95.61

Classifying cities over the earth: can CNNs generalize?

Inria Aerial Image Labeling Dataset: first outcomes

- Intersection over union improved from 55.82% to **78.39%**
- The most commonly used successful architecture: **U-Net**
    - AMLL, Duke University: original U-Net with half as many filters



B Huang et al. "Large-scale semantic classification: Outcome of the first year of Inria aerial image labeling benchmark". IGARSS 2018.

Classifying cities over the earth: can CNNs generalize?

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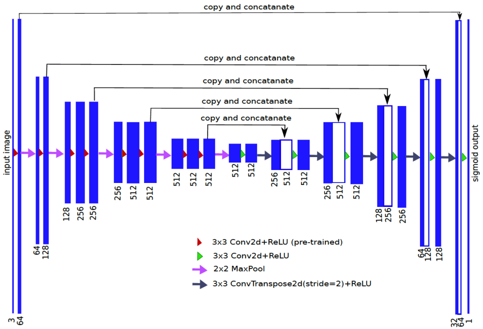
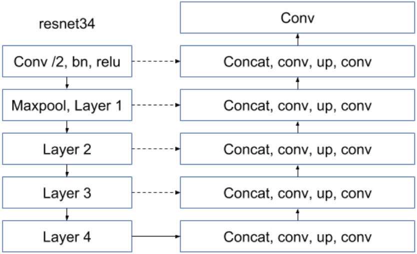
  - Vladimir Iglovikov: TernausNet with VGG11-like encoder



Classifying cities over the earth: can CNNs generalize?

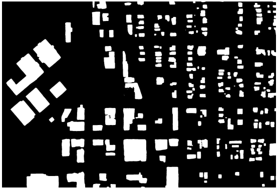
Inria Aerial Image Labeling Dataset: first outcomes

- Intersection over union (IoU) improved from 55.82% to **78.39%**
- **Winning architecture:**



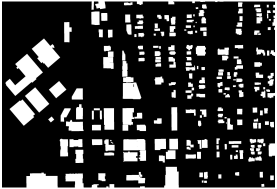
Inria Aerial Image Labeling Dataset outcomes (IoU, %)

RGB image

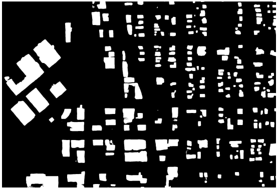


A. Buslaev (78.39)

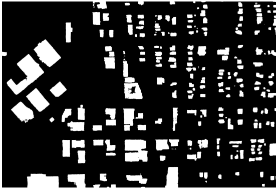
V.Iglovikov (75.28)



Ground truth



AMLL (72.55)



Onera (71.02)

B Huang et al. "Large-scale semantic classification: Outcome of the first year of Inria aerial image labeling benchmark". IGARSS 2018.

Classifying cities over the earth: can CNNs generalize?

How to achieve good results?

- Right choice of architecture: U-net for semantic labeling
- Right choice of loss function: combination of cross-entropy & IoU
- Right choice of training strategy
- Right choice of other parameters: learning rate, size of batch, ...

Common loss functions

Loss function quantifies the misclassification by comparing the target label vectors $\mathbf{y}^{(i)}$ and the predicted label scores $\hat{\mathbf{y}}^{(i)}$, for n training samples

- **Cross-entropy loss**:

$$L_{CE} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{|\mathcal{L}|} y_k^{(i)} \log \hat{y}_k^{(i)}$$

  - has fast convergence rates when training neural networks
  - numerically stable when coupled with softmax normalization

- Differentiable soft IoU loss*:

$$L_{IoU} = \frac{1}{|\mathcal{L}|}\sum_{\mathcal{L}} \frac{\sum_i \hat{y}_k^{(i)} \cdot y_k^{(i)}}{\sum_i \hat{y}_k^{(i)} + y_k^{(i)} - \hat{y}_k^{(i)} \cdot y_k^{(i)}}$$

  - enforces network to push predictions to 0 and 1

Mattyus et al. "Deeproadmapper: Etracting road topology from aerial images". ICCV 2017.

Classifying cities over the earth: can CNNs generalize?

How to achieve good results?

- Right choice of architecture: U-net for semantic labeling
- Right choice of loss function: combination of cross-entropy & IoU
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- Right choice of other parameters: learning rate (e.g. cyclic), size of batch, ...

Classifying cities over the earth: can CNNs generalize?

How to achieve good results?

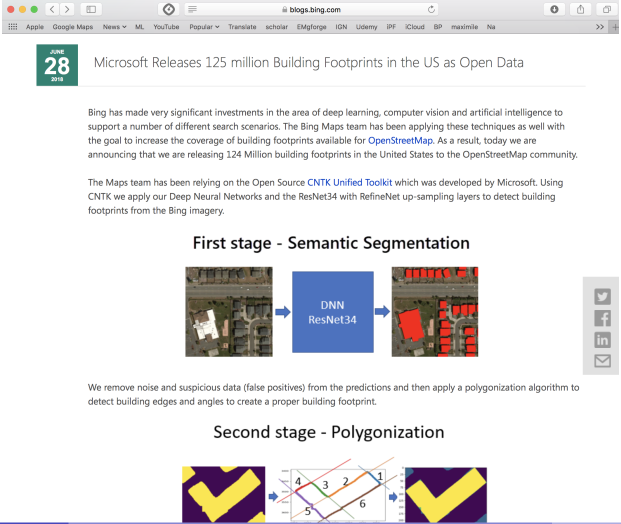
- Right choice of architecture: U-net for semantic labeling
- Right choice of loss function: combination of cross-entropy & IoU
- Right choice of training strategy
- Right choice of other parameters: learning rate (e.g. cyclic), size of batch, ...
- **Good training dataset!**

Where to get data?

- A lot of available aerial and satellite imagery!
  - Example: Sentinel
    `https://sentinel.esa.int/web/sentinel/home`
  - Difficult and expensive to get ground-truth data
- Solutions?
  - Use available datasets/benchmarks
    - IARPA challenge: 3.5TB satellite multispectral data, 62 classes
    - CrowsAI challenge: $>$ 300K 300 $\times$ 300 RGB satellite images & building annotations
      https://www.crowdai.org/challenges/mapping-challenge
  - Use crowd-sourced maps
    - `http://www.openstreetmap.org`
    - `https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-urban-atlas`

Where to get data?

- Solutions?
  - Use maps predicted with deep learning nets and released as open data?



blogs.bing.com

JUNE 28 2018

Microsoft Releases 125 million Building Footprints in the US as Open Data

Bing has made very significant investments in the area of deep learning, computer vision and artificial intelligence to support a number of different search scenarios. The Bing Maps team has been applying these techniques as well with the goal to increase the coverage of building footprints available for OpenStreetMap. As a result, today we are announcing that we are releasing 124 Million building footprints in the United States to the OpenStreetMap community.

The Maps team has been relying on the Open Source CNTK Unified Toolkit which was developed by Microsoft. Using CNTK we apply our Deep Neural Networks and the ResNet34 with RefineNet up-sampling layers to detect building footprints from the Bing imagery.

First stage - Semantic Segmentation

We remove noise and suspicious data (false positives) from the predictions and then apply a polygonization algorithm to detect building edges and angles to create a proper building footprint.

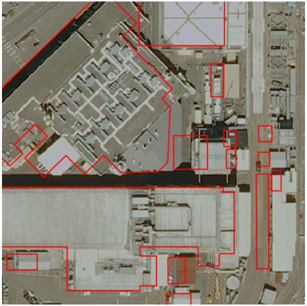
Second stage - Polygonization

Dealing with imperfect training data

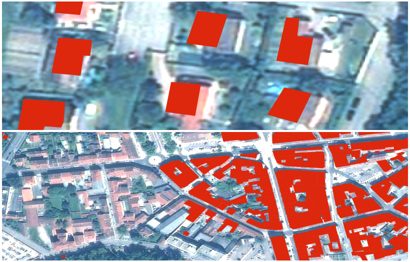
And if training dataset is not good enough?

Dealing with imperfect training data

- Frequent misregistration/omission in large-scale data sources
  - Example: OpenStreetMap data are mostly misaligned with satellite data



Dealing with imperfect training data

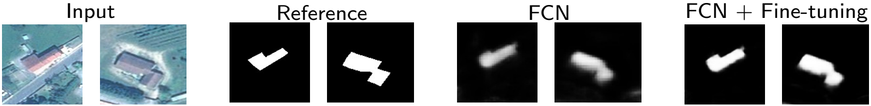


Pléiades image + OpenStreetMap (OSM)

Proposed method

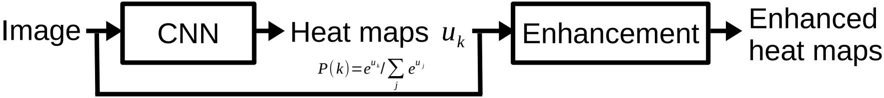
Two-step training process:

1. Pretrain on large amounts of imperfect data
   → Learn dataset generalities
2. Fine-tune on a small piece of manually labeled reference



E. Maggiori, Y. Tarabalka, G. Charpiat, P. Alliez. "Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification", TGRS 2017.

Enhancing CNNs' outputs



Recent approaches

- CNN + Fully connected CRF (Chen et al., ICML 2015)
- CNN + Fully connected CRF as RNN (Zheng et al., CVPR 2015)
- CNN + Domain transform (Chen et al., CVPR 2016)

In remote sensing:

- CNN + CRF (Paisitkriangkrai et al., CVPR Worshops 2015)
- CNN + fully connected CRF (Marmanis et al., ISPRS 2015; Sherrah 2016,...)

Goal

Learn iterative enhancement process

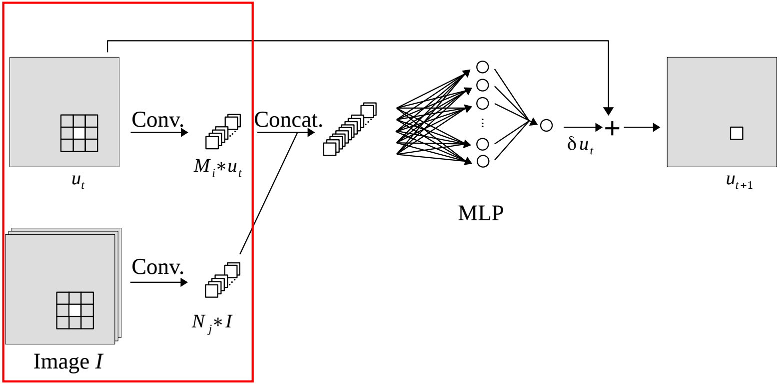
Partial differential equations (PDEs)

Given heat maps u_k, image I:

- Heat flow
  (Smooths out u_k)
  $$\frac{\partial u_k(x)}{\partial t} = \mathrm{div}(\nabla u_k(x))$$
- Perona-Malik
  Edge-stopping function $g(\nabla I, x)$
  $$\frac{\partial u_k(x)}{\partial t} = \mathrm{div}(g(\nabla I, x)\nabla u_k(x))$$
- Anisotropic diffusion
  Diffusion tensor $D(I, x)$
  $$\frac{\partial u_k(x)}{\partial t} = \mathrm{div}(D(\nabla I, x)\nabla u_k(x))$$
- Geodesic active contours
  Edge-stopping function $g(\nabla I, x)$
  $$\frac{\partial u_k(x)}{\partial t} = |\nabla u_k(x)|\mathrm{div}\left(g(\nabla I, x)\frac{\nabla u_k(x)}{|\nabla u_k(x)|}\right)$$
- ...

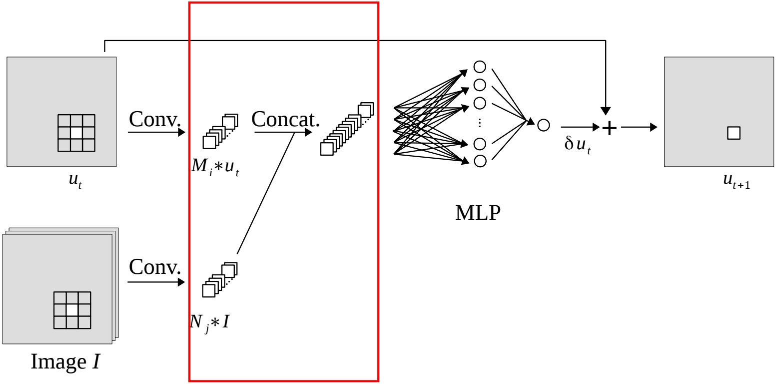
A generic enhancement process

- Differential operations $\left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}, \frac{\partial^2}{\partial x \partial y}, \frac{\partial^2}{\partial x^2}, \ldots\right)$ applied on u_k and image I
- Implemented as convolutions: $M_i * u_k$, $N_j * I$
  $\{M_1, M_2, \ldots\}$, $\{N_1, N_2, \ldots\}$ conv. kernels (e.g., Sobel filters)



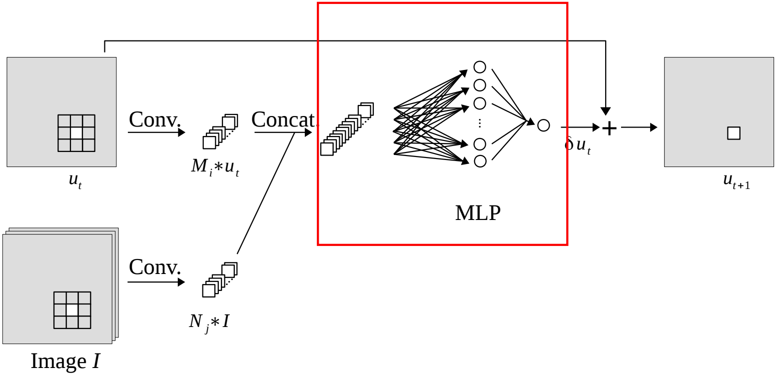
A generic enhancement process

- $\Phi(u_k, I) = \{M_i * u_k,\ \ N_j * I\ ;\ \ \forall i, j\}$, set of responses



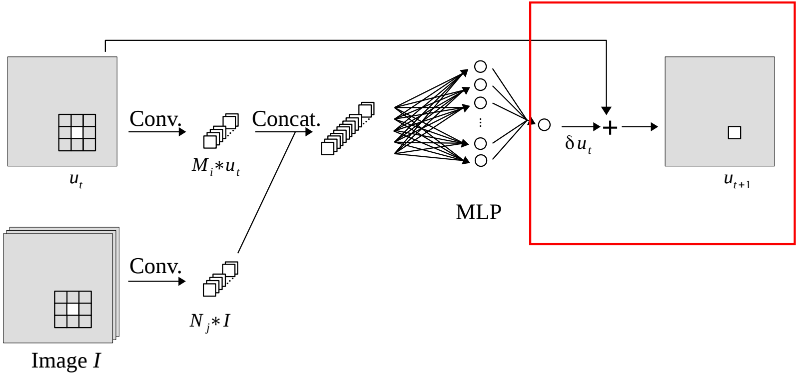
A generic enhancement process

- Overall update on u_k at x: $\delta u_k(x) = f_k\ (\ \Phi(u_k, I)(x)\ )$
- Class-specific f_k, implemented as multilayer perceptron
- M_i and N_j convey spatial reasoning (e.g., gradients), f_k their combination (e.g., products)



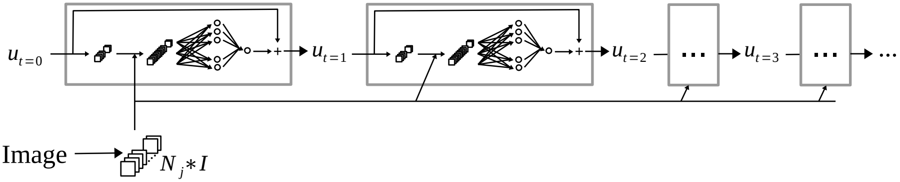
A generic enhancement process

- Discretized in time:
  $u_{k,t+1}(x) = u_{k,t}(x) + \delta u_{k,t}(x)$, overall update δ



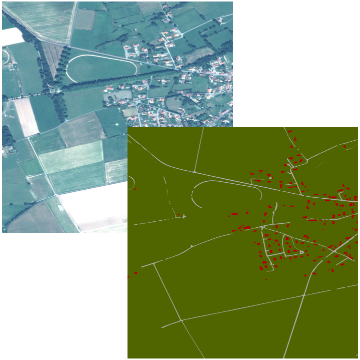
Iterative processes as recurrent neural networks (RNNs)

- "Unroll" iterations
- Every iteration is meant to progressively refine the classification maps
- Enforce weight sharing along iterations
- Train by backpropagation ("through time")



Experiments

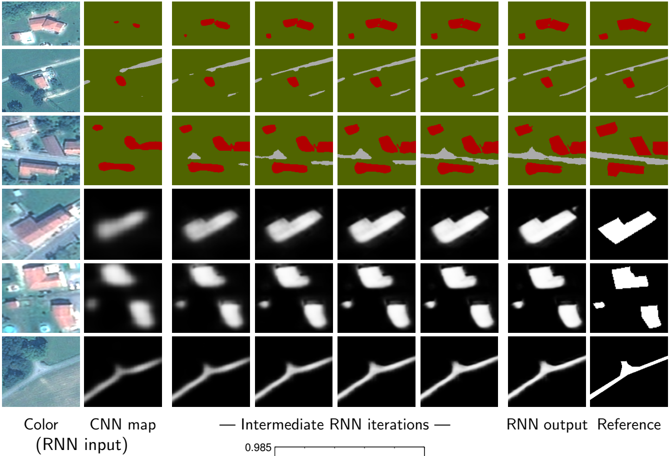
- FCN trained on Pléiades + OSM data
- Manually labeled tiles
  for RNN training/testing
- Unroll 5 iterations
- 32 M_i and 32 N_j
- MLP: 1 hidden layer, 32 neurons

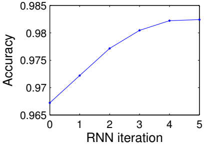


Building, Road, Background

E. Maggiori, G. Charpiat, Y. Tarabalka, P. Alliez. "Recurrent Neural Networks to Correct Satellite Image Classification Maps". TGRS 2017.

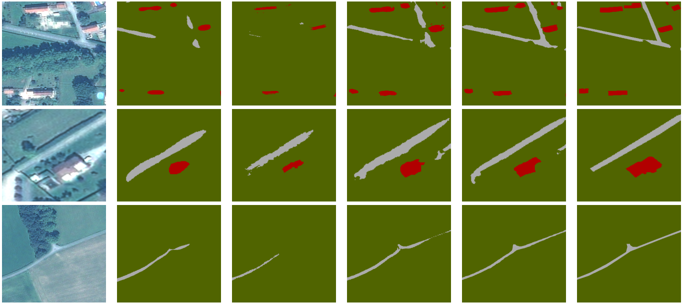
Experiments





Experiments

Comparison

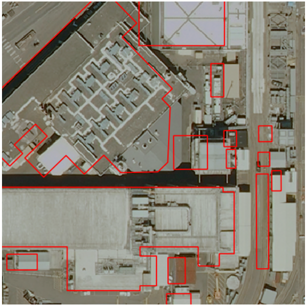


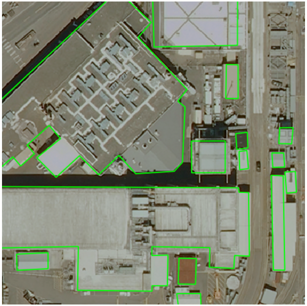
Color image | Coarse CNN | CNN+CRF | Class-agnostic CNN+RNN | CNN+RNN | Reference

Method	Overall accuracy	Mean IoU	Class-specific IoU Build.	Road	Backg.
CNN	96.72	48.32	38.92	9.34	96.69
CNN+CRF	96.96	44.15	29.05	6.62	96.78
Class-agn. CNN+RNN	97.78	65.30	59.12	39.03	97.74
CNN+RNN	**98.24**	**72.90**	**69.16**	**51.32**	**98.20**

Fully-convolutional net for multimodal image registration

- **Could we train a neural net to solve image-map alignment problem?**

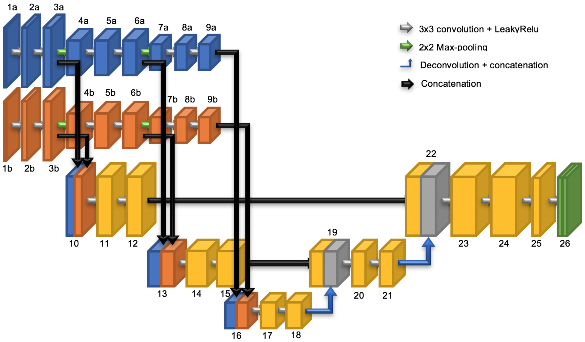




A. Zampieri, G. Charpiat, N. Girard, Y. Tarabalka. "Multimodal image alignment through a multiscale chain of neural networks with application to remote sensing", ECCV 2018.

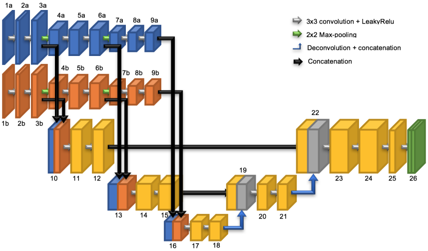
Fully-convolutional net for multimodal image registration

- Fully-convolutional neural net for image-map alignment



- Image is fed to 1a, rasterized map is fed to 1b
- Output: 2-dimensional vector map representing a deformation field

Fully-convolutional net for multimodal image registration



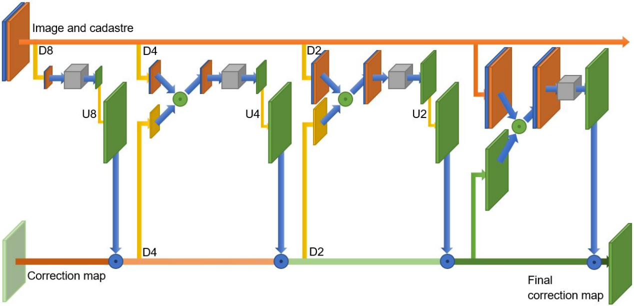
- Loss function: Euclidean norm of the prediction error

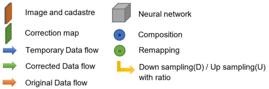
$$C = \mathop{\mathbb{E}}_{(I_1,I_2,\phi_{\mathrm{GT}})\in\mathcal{D}} \left[\sum_{\mathbf{x}\in\Omega(I_2)} \left\| \widehat{\phi}_{(I_1,I_2)}(\mathbf{x}) - \phi_{\mathrm{GT}}(\mathbf{x}) \right\|_2^2 \right],$$

i.e., expectation, over the ground truth dataset $\mathcal{D}$ of triplet examples (RGB image I_1, cadastral image I_2, associated deformation ϕ_{GT}), of the sum, over all pixels $\mathbf{x}$ in the image domain $\Omega(I_2)$, of the norm of the difference between the ground truth deformation $\phi_{\mathrm{GT}}(\mathbf{x})$ and the one predicted $\widehat{\phi}_{(I_1,I_2)}(\mathbf{x})$ for (I_1, I_2)

Fully-convolutional net for multimodal image registration

- Chain of scale-specific neural nets for image-map alignment

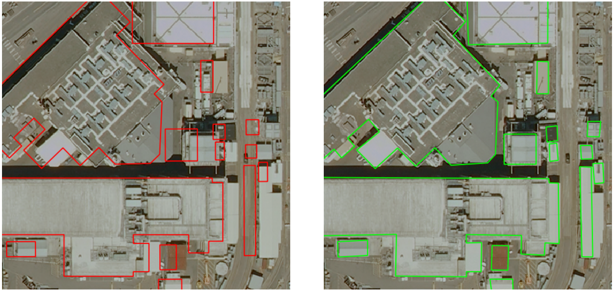


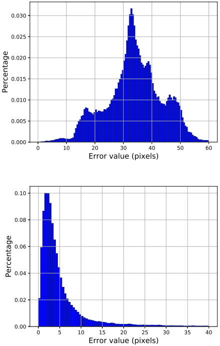


- Main idea: each scale-specific block:
  - downsamples the images to the right size,
  - applies the previously-estimated deformation,
  - refines it

Fully-convolutional net for multimodal image registration

- Chain of scale-specific neural networks to solve alignment problem

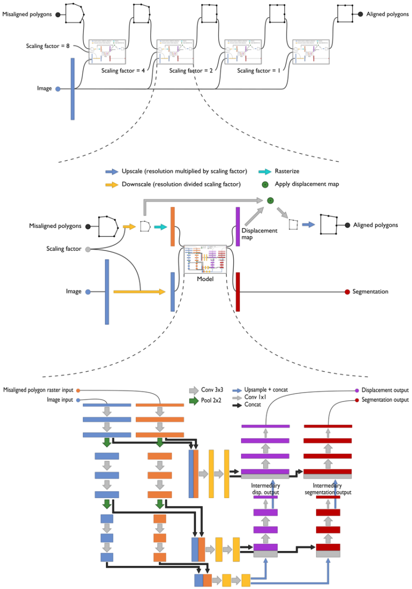




Misalignment distribution
before and after processing

A. Zampieri, G. Charpiat, N. Girard, Y. Tarabalka. "Multimodal image alignment through a multiscale chain of neural networks with application to remote sensing", ECCV 2018.

Align and update maps in one net?

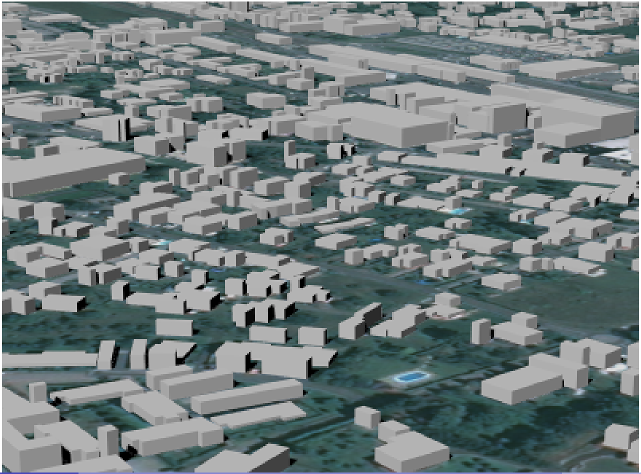


- Multi-resolution snd multi-task deep learning
- Modified U-Net to have 2 image inputs and 2 image outputs
- Output: aligned and updated cadaster map

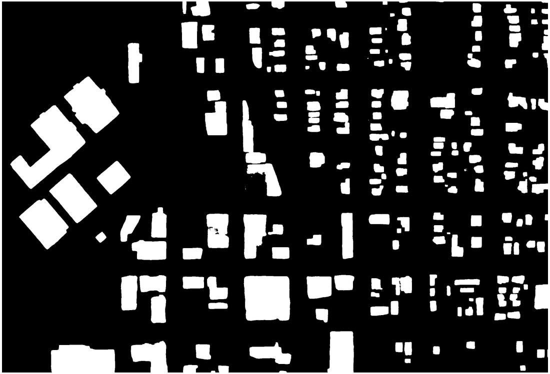
N. Girard et al., "Aligning and updating cadaster maps with aerial images by multi-resolution, multi-task deep learning", ACCV 2018.

Application: 2.5D reconstruction of buildings

- From a stereo pair of images
- Height estimation by alignment of polygons of one view to the image of the other view, and vice versa

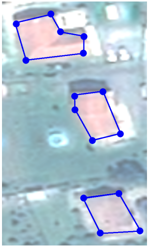


How to update GIS with the created maps?



Input image → **Classification** → Classif. map → **Polygonization** → Shapefile

- Polygonization of classification maps
  $\rightarrow$ incorporate objects into GIS

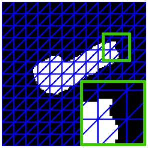


From raster to polygons

- Polygonization of classification maps $\rightarrow$ incorporate objects into GIS
- Typically (QGIS, GRASS, ArcGIS,...): greedy simplification algorithms

Using mesh approximation

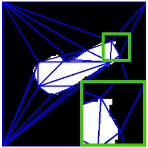
- Goal: approximate objects with (labeled) triangular mesh
- Integral formulation



Fine lattice

$\rightarrow$

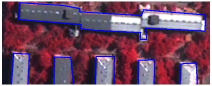
Opt.

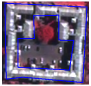


Approximation

Optimization algorithm

- Discrete mesh operators (edge flip/collapse)
- Continuous vertex relocation
- Topology preservation & geometric regularity





O. Tasar et al., "Polygonization of binary classification maps using mesh approximation with right angle regularity," IGARSS'18

Can we learn in a vector space?

Analyzing this new paradigm

Several tasks:

- Object detection
- Object recognition
- Object polygon outline regression

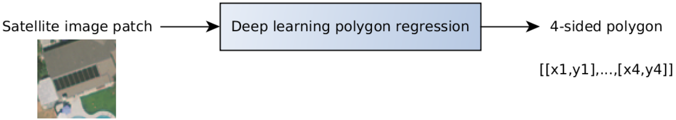
Difficulties:

- Thousands of objects per satellite image
- Variable amount of objects across images
- Variable amount of vertices across polygons
- Overlapping objects

Problem statement

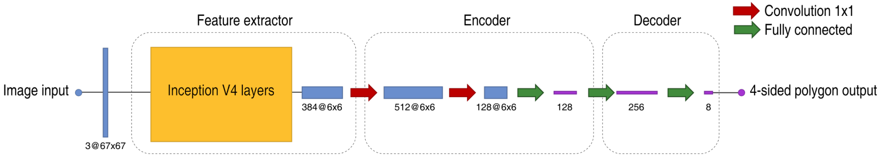
Reduced goal:

- Task: object polygon outline regression
- Input: image patch centered on a detected object of one class
  - Output of an object detector like Faster-RCNN:
- Output: one polygon outlining the object
  - Number of vertices fixed to 4



S. Ren et al., Faster R-CNN: towards real-time object detection with region proposal networks, 2015.

Polygon regression neural network *PolyCNN*

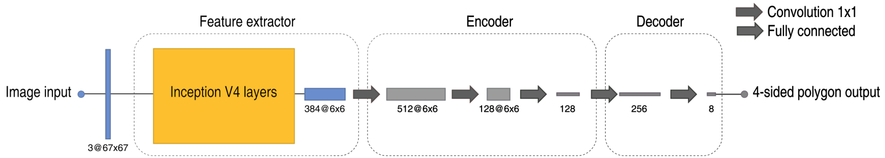


Three blocks:

1. Feature extractor
2. Encoder
3. Decoder

N. Girard & Y. Tarabalka. "End-to-end learning of polygons for remote sensing image classification," IGARSS 2018.

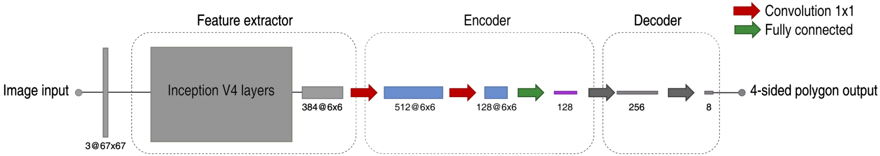
1. Feature extractor



Pre-trained Inception V4 layers used:

C. Szegedy et al., Inception-v4, inception-resnet and the impact of residual connections on learning, 2016.

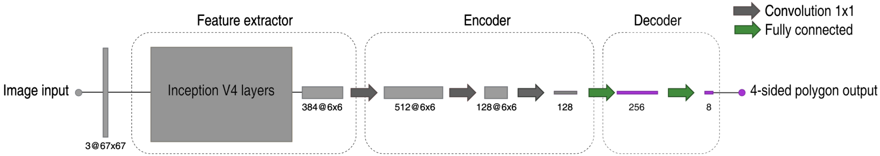
2. Encoder



Encodes object outline in a vector of 128 dimensions:

- A point in a latent space
- Represents the object shape

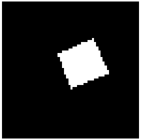
3. Decoder



Decodes the 128-dimensions vector into polygon coordinates:

- 4 vertices in $2D = 8$ scalars

Finding the right architecture for the encoder and decoder



Creation of an artificial dataset:

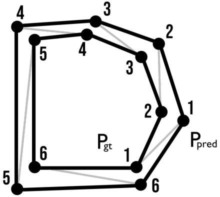
- Random 4-sided polygons as ground truth
- Rasterized polygons as image input

Infinite amount of simple examples:

- Fast training, only a simple feature extractor is needed
- Test architectures to find the smallest encoder and decoder that work
- Pre-train decoder

Loss

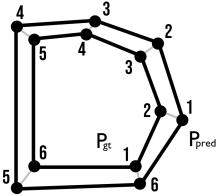
Network trained by supervised learning, naive loss:



$$L = \frac{1}{n} \sum_{i=1}^{n} \| \mathbf{P_{gt}}(\mathbf{i}, .) - \mathbf{P_{pred}}(\mathbf{i}, .) \|_2 \tag{1}$$

Loss

Network trained by supervised learning, corrected loss:



$$L = \min_{\forall s \in [0, n-1]} \frac{1}{n} \sum_{i=1}^{n} \|\mathbf{P_{gt}}(\mathbf{i}, .) - \mathbf{P_{pred}}(\mathbf{i} + \mathbf{s}, .)\|_2 \tag{2}$$

Dataset

Solar panel dataset from Bradbury et al. from Duke University:

- 601 aerial images of 5000×5000 px
- Ground truth polygons of photovoltaic arrays
- Polygons precisely annotated manually
- Over 19000 solar panels
- Over 6000 4-sided ground truth polygons
- 256 polygons for validation and another 256 for testing

K. Bradbury et al., Distributed solar photovoltaic array location and extent dataset for remote sensing object identification, 2016.

Training

1. Feature extractor pre-trained on ImageNet
2. Encoder initialized randomly
3. Decoder pre-trained on the artificial dataset

Learning rate schedule:

learning rate up to iteration	500	1000	90000
Feature extractor	0	0	$1e^{-5}$
Encoder	$1e^{-5}$	$1e^{-5}$	$1e^{-5}$
Decoder	0	$1e^{-5}$	$1e^{-5}$

- Random weights produce big gradients at the start of training
- Avoid rapid distortion of pre-trained weights by freezing them in the beginning

J. Deng et al., ImageNet: A Large-Scale Hierarchical Image Database, 2009.

Visual results

Test on image patches never seen by the network:

PolyCNN

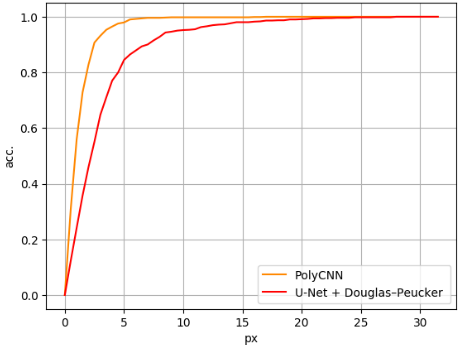
U-Net
+ Douglas-Peucker

Green: ground truth, orange: PolyCNN output and red: U-Net + Douglas-Peucker output

Quantitative results

	PolyCNN	U-Net + Douglas-Peucker
mIoU	79.5%	62.4%

For any threshold τ we compute the fraction of vertices whose ground truth point distance is less than τ:



Conclusions & Perspectives

There is no such thing as a universally better classifier

- To classify images on a world-scale:
  - Learning methods must be **generic** and **highly scalable**
  - CNNs have shown a remarkable computational performance
    - Capable to learn expressive multi-scale contextual features
    - Succeed in classifying new unseen earth areas
  - Still significant work to be done to design automatic mapping systems
    - New powerful models: adversarial networks, unsupervised & semi-supervised learning, capsule nets