Exploiting contextual features in superpixels for land cover mapping using high resolution image time series

Phi-Week 2018

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Context

- Large-scale land cover mapping

- Annual summer crops
- Annual winter crop
- Broad-leaved forest
- Coniferous forest
- Natural grasslands
- Woody moorlands
- Continous urban fabric
- Discontinuous urban fabric
- Industrial or commercial units
- Road surfaces
- Water bodies
- Intensive grassland
- Orchards
- Vineyards

Context

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- Series of Sentinel-2 images
  - 110km $\times$ 110km at 10m
  - 13 spectral features / date
  - 33 dates (year : 2016)
  - 489 features
  - Approximately 90Gb

Context

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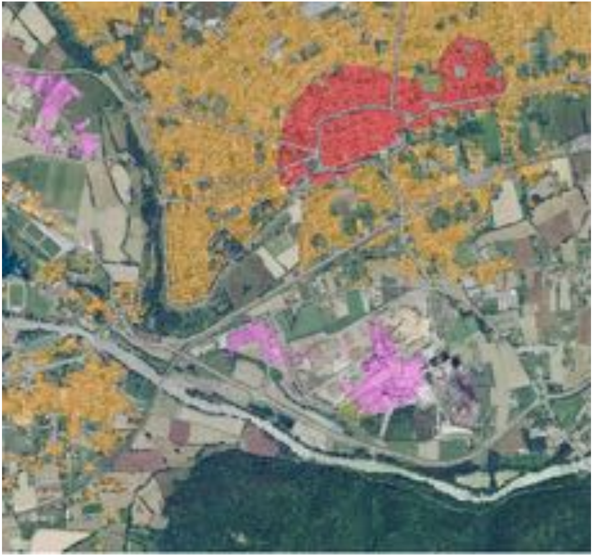
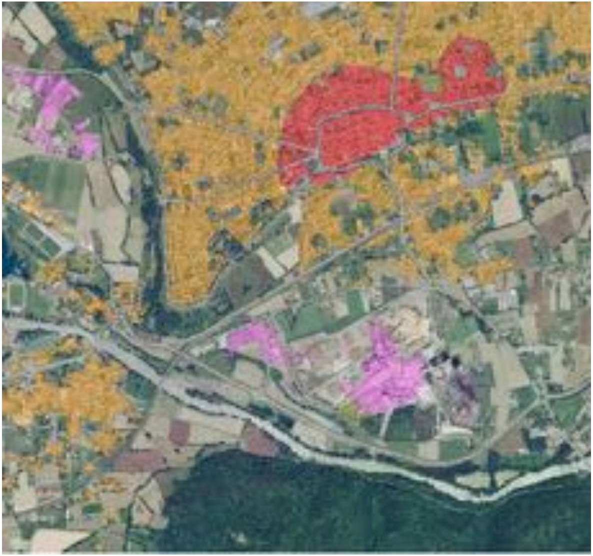
- Series of Sentinel-2 images
  - 110km $\times$ 110km at 10m
  - 13 spectral features / date
  - 33 dates (year : 2016)
  - 489 features
  - Approximately 90Gb
- This description is not sufficient to separate all of the desired land cover classes

Context



- Continous urban cover (red)
- Diffuse urban cover (orange)
- Industrial and commercial areas (mauve)

Context



- Continous urban cover (red)
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- Industrial and commercial areas (mauve)
- The difference lies in the context of the pixel

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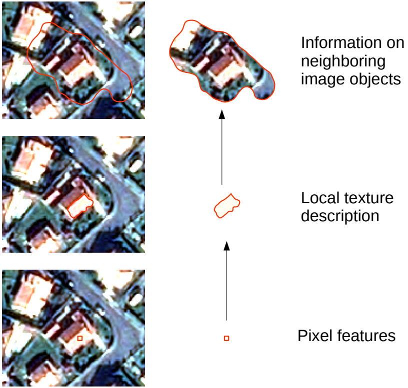
Context

- Popular approach nowadays
  - Deep Convolutional Neural Network (D-CNN)
    - Context implicit in the first layers
    - Has proven to be accurate on many problems
    - Heavy computational load
- Operational context, large data volumes
- Speed and efficiency are essential
- Can the same performance be achieved with alternative methods ?

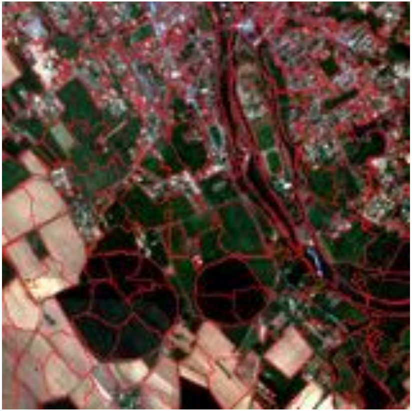
Proposed method

- Using features from superpixel neighborhoods at one or several scales



Superpixels : illustration

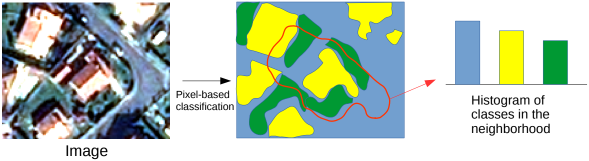
SLIC superpixel segmentation



Mean Shift segmentation

Auto-Context

- From an initial pixel-based classification, we can calculate the histogram of the classes in one or several neighborhoods



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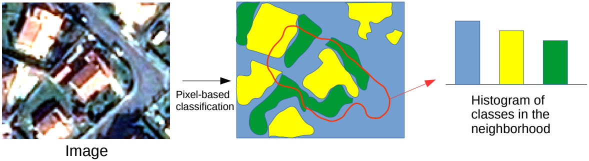
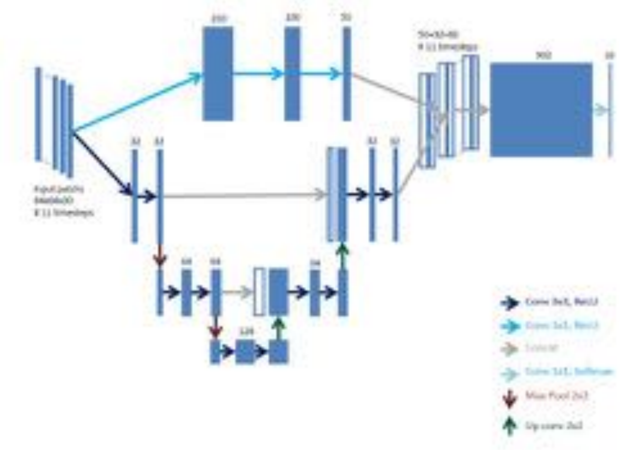


  - This histogram is used as a feature for generating a new classification
  - The process can be iterated several times
- Compact feature (14 vs 330 dimensions)
- Adapted for use multi-scale application

Deep Convolutional Network

- U-net type architecture adapted to time series classification
- Combined with fully connected, pixel resolution MLP
- Weight sharing in the first layers



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Results

- Tests on 4 different 110x110 km areas

	Kappa	OA
T31TDN		
RF (pixel)	89,53 %	91,87 %
AC	89,42 %	92,19 %
MLP_Unet	89,82 %	92,49 %
T30TXQ		
RF (pixel)	82,87 %	90,61 %
AC	86,90 %	93,31 %
MLP_Unet	87,74 %	93,77 %
T31TGK		
RF (pixel)	64,24 %	71,01 %
AC	66,66 %	73,10 %
MLP_Unet	67,20 %	73,67 %
T31UDQ		
RF (pixel)	75,02 %	79,40 %
AC	84,70 %	88,70 %
MLP_Unet	86,13 %	89,78 %

Table: Computation times

Method	Training time/CPU
RF	≈25h
Auto-Context	≈80h
MLP-Unet	≈3300h

Results

Image, first date, RGB channels

- Annual summer crops
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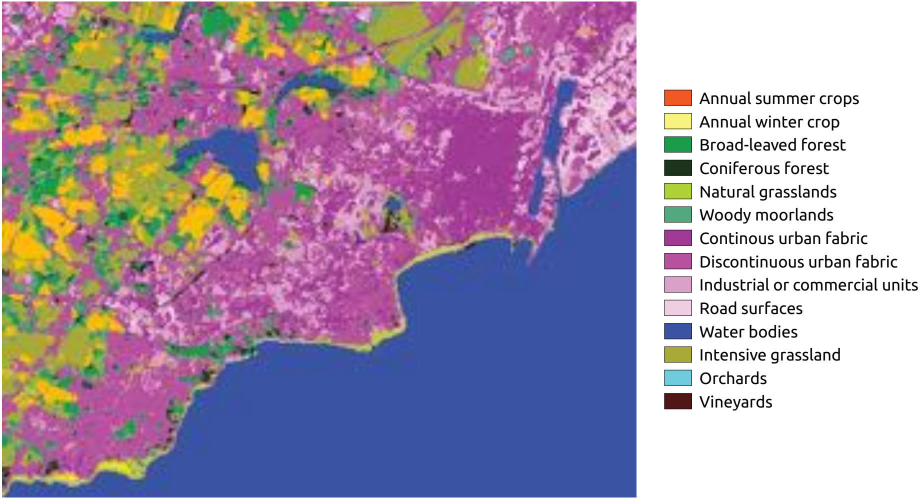
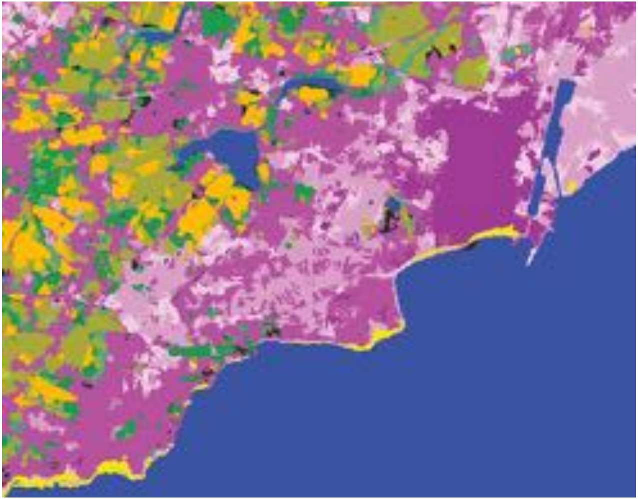
Results

Pixel based classification (Random Forest)



Results

Auto-Context histograms



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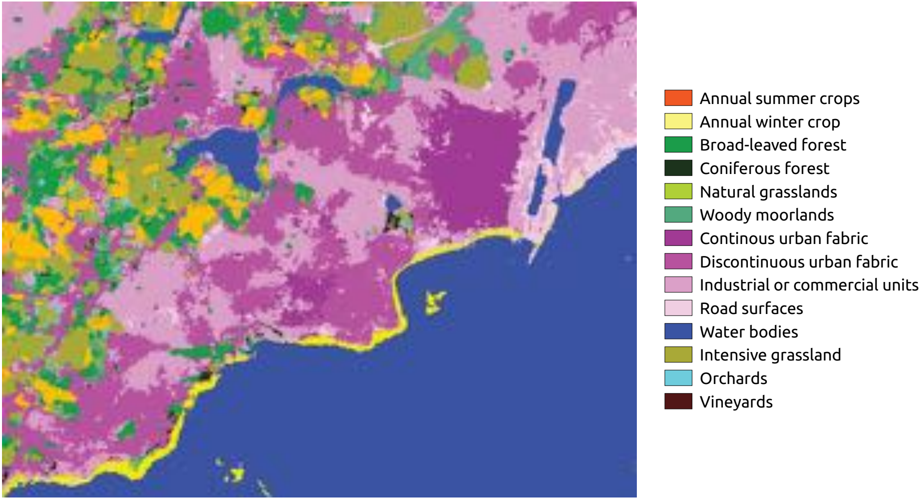
Results

MLP-Unet



Results

Image

RF

Auto-Context

MLP-Unet

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Conclusion and perspectives

- Deep Convolutional Neural Network
  - Strongest results on urban classes
  - Also deteriorates some other classes
- Superpixel + Auto-Context histograms
  - Similar overall performance to Deep Learning methods
  - Consistent improvement on all classes
  - Lower computational burden
- Can be an alternative to Deep Learning
- Should be validated further
  - Wider range of Sentinel-2 areas
  - Very High Resolution Pleiades images

Thank you for your attention