3D Classification of Crossroads from Aerial Images using Conditional Random Fields

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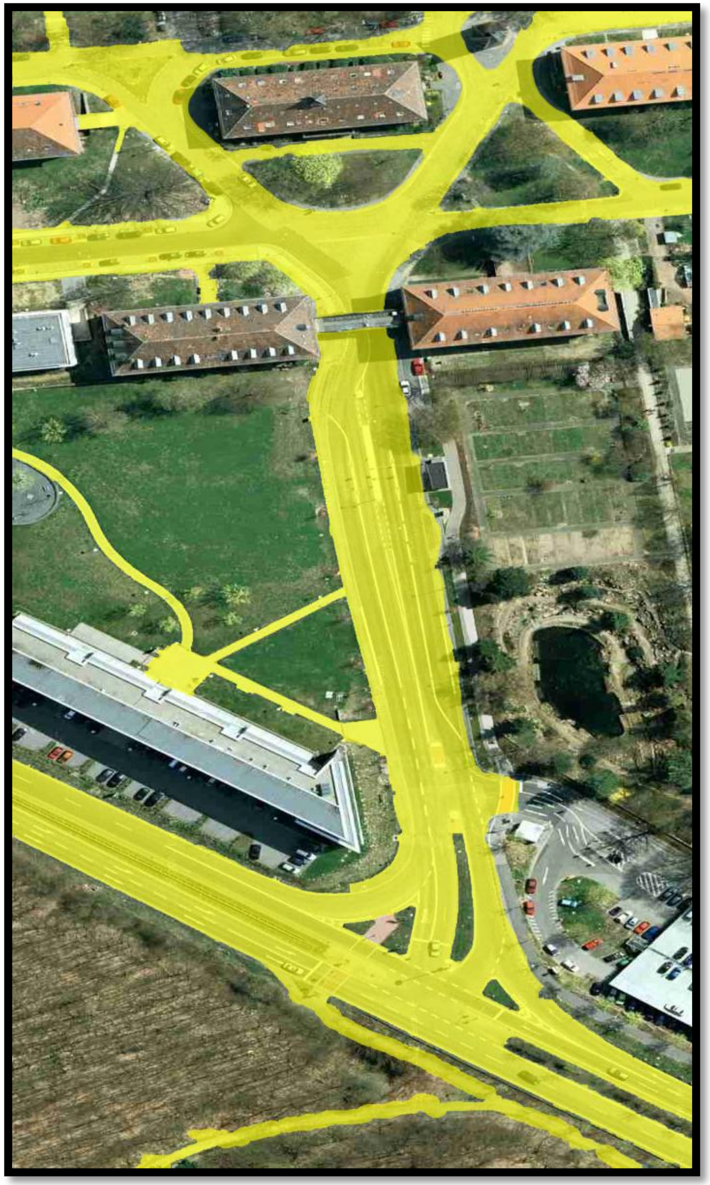
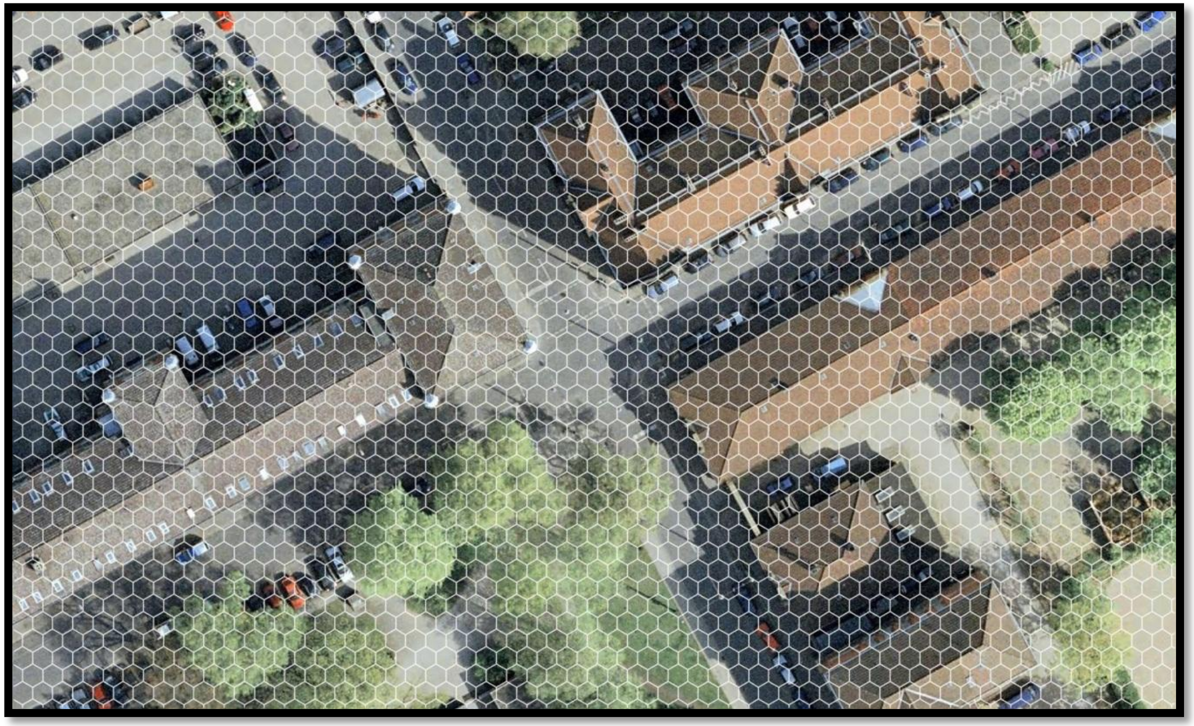


Overview

1. Conditional Random Fields
2. Input Data and Features
3. Association and Interaction Potential Functions
4. Experimental Results

Graphical Model

- Graphical Model
  - Nodes are image pixels, sites, segments.
  - Edges are structure relations

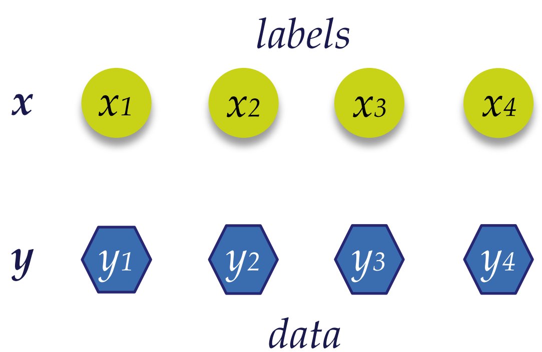


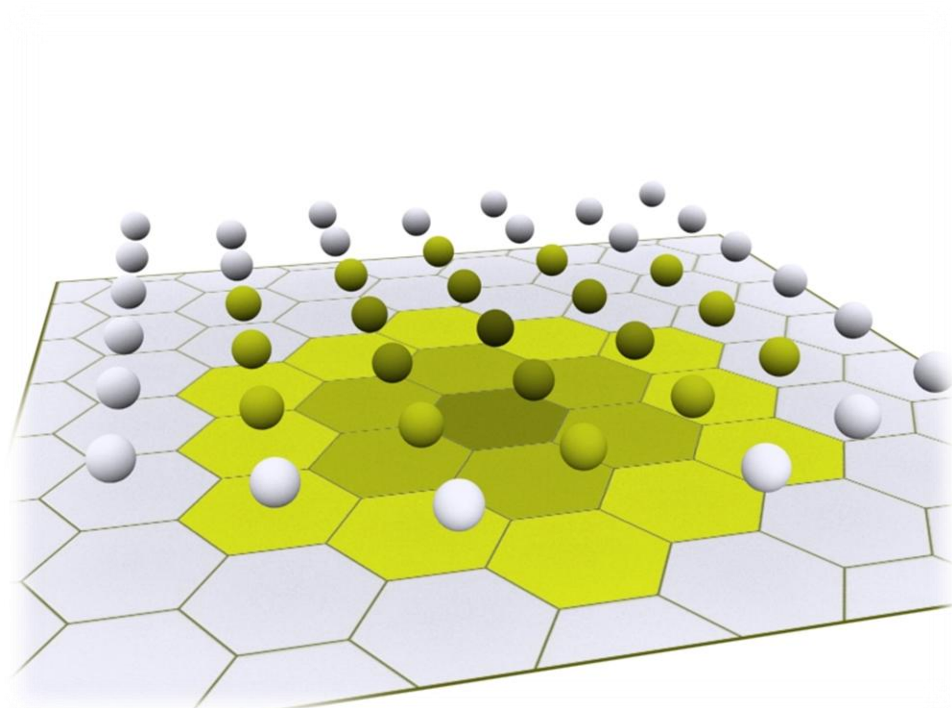
Conditional Random Fields

- Conditional random field is a statistical modeling method based on discriminative undirected probabilistic graphical model.

$$p(\mathbf{x}|\mathbf{y}) = \frac{1}{Z} \cdot exp\left[\sum_c \phi_c(x_c, y_c)\right]$$

  - x_c label ; y_c data
  - ϕ_c potential function
  - Z partition function



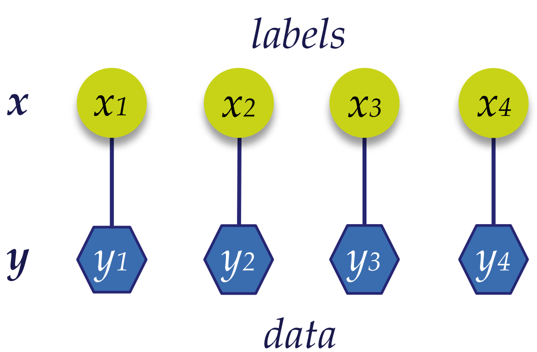


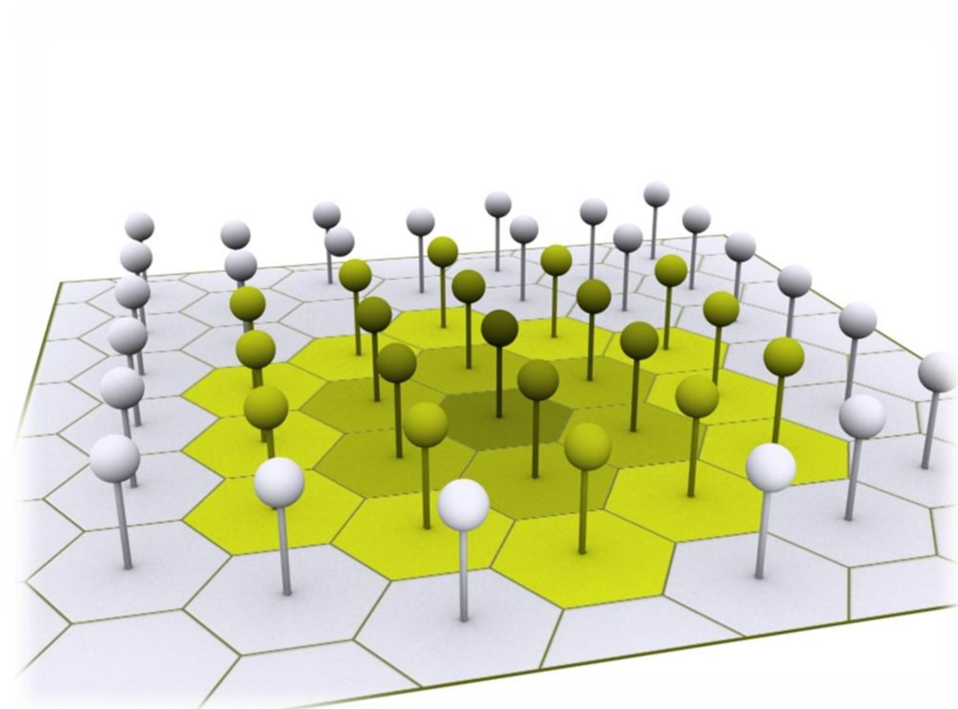
Conditional Random Fields

- Association potential function is a function of all data, not only of the features of the site

$$p(\mathbf{x}|\mathbf{y}) = \frac{1}{Z} \cdot exp\left[\sum_i \varphi_i(x_i, \mathbf{y})\right]$$

  - x_i label ; $\mathbf{y}$ data
  - φ_i association potential
  - i data site index



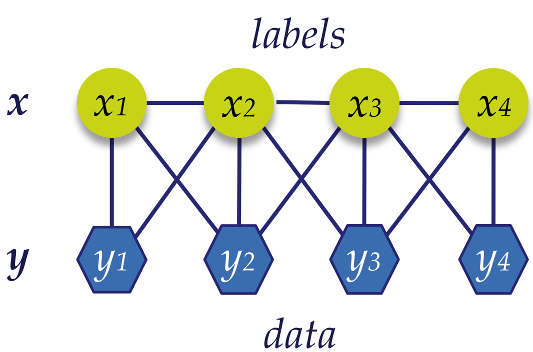


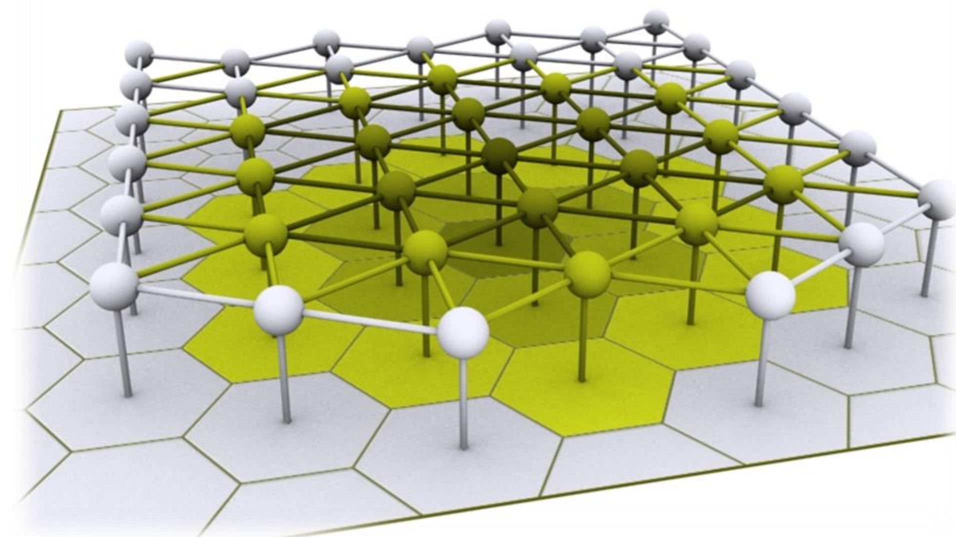
Conditional Random Fields

- Interaction potential function is not only a function of labels but also of features.

$$p(\mathbf{x}|\mathbf{y}) = \frac{1}{Z} \cdot exp\left[\sum_i \varphi_i(x_i, \mathbf{y}) + \sum_i \sum_{j \in \aleph_i} \psi_{ij}(x_i, x_j, \mathbf{y}) \right]$$

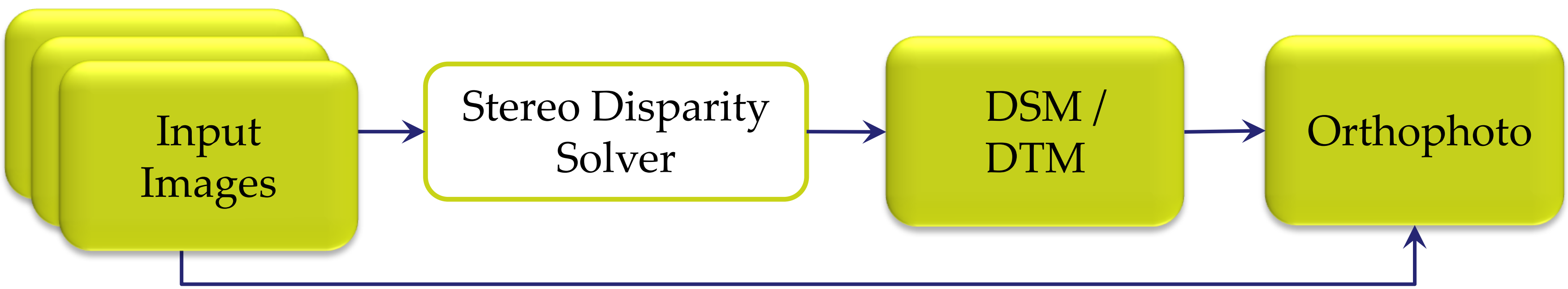
  - x_i label ; $\mathbf{y}$ data
  - ψ_i interaction potential
  - N_i neighborhood of i



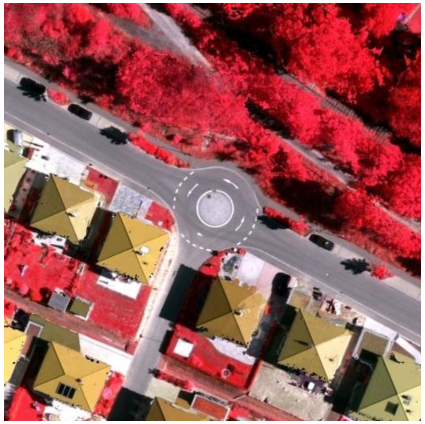


Data Pipeline

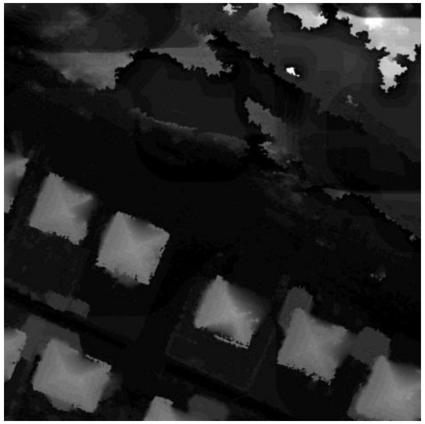
- Input data for one cross-road:
  - At least 4 airborne images with infra-red channel
  - Image overlapping at least 60%
  - Ground sampling distance: ~15 cm
- Derived data for one cross-road:
  - Digital Surface / Terrain Model (DSM / DTM)
  - Orthophoto

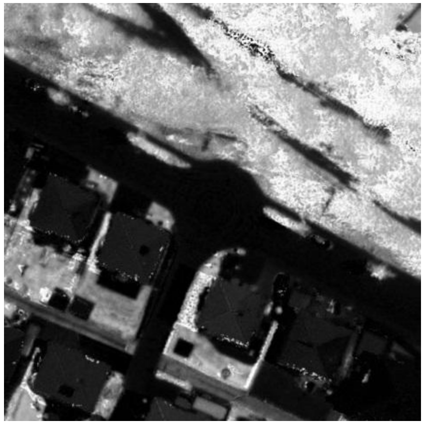


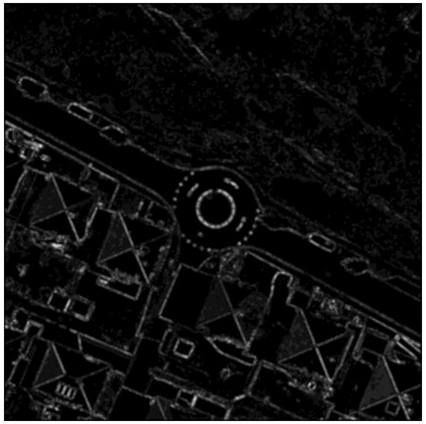
Data Features

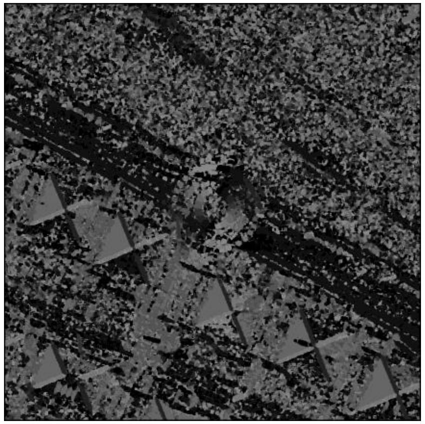

Original image


Inverse of hue


DSM - DTM


NDVI

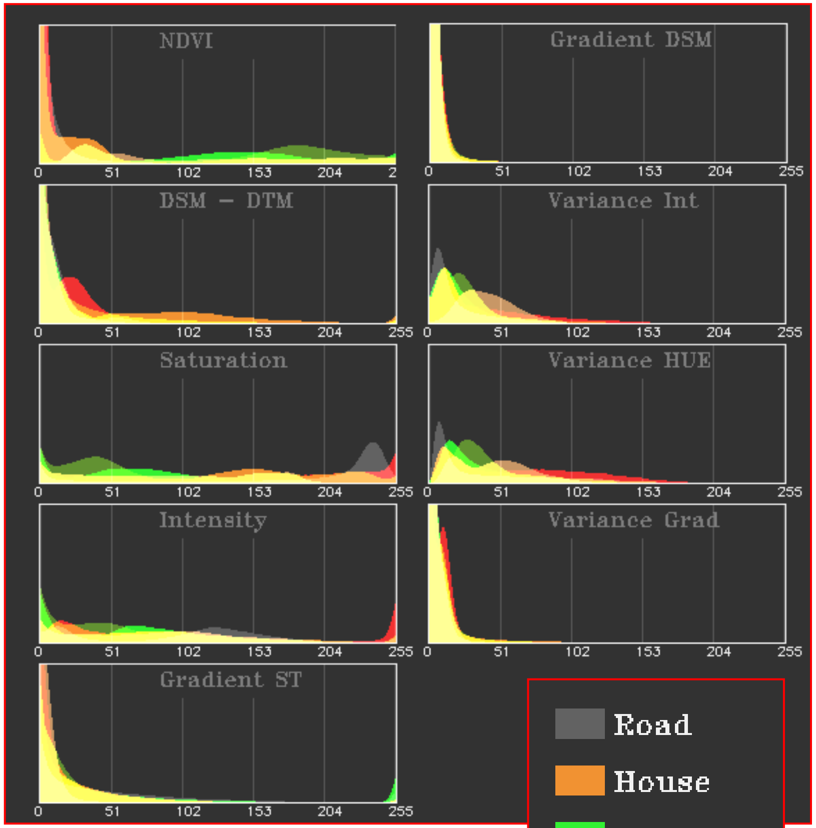

Magnitude of gradient


Orientation of gradient

Association Potential

- How likely is a node x_i has label c ignoring the other nodes:
  $\varphi\ (x_i, \mathbf{y}) = \log p(x_i = c \mid \mathbf{f}_i(\mathbf{y}))$
- A Bayesian classifier:
  $p(x_i = c \mid \mathbf{f}_i(\mathbf{y})) \propto p(\mathbf{f}_i(\mathbf{y}) \mid x_i = c)$
- Generate 1D histograms for each class and each feature:
  $p(f_{ij} \mid x_i = c) \equiv p_c\ (f_{ij} \mid x_i)$

$$\varphi\ (x_i = c, \mathbf{y}) = \sum_{j=1}^{N} \log\left[p_c\left(f_{ij} \mid x_i\right)\right]$$



Visualisation of the PDF histograms for 6 classes and 9 features.

Interaction Potential

- Measure for the influence of neighbouring sites
- Generate a 2D histogram of the coocurances of labels at neighbouring image sites: $h(x_i, x_j)$
- Calculate an Euclidian Distance between features from neighbouring image sites: $d_{ij} = ||\mathbf{f}_i(\boldsymbol{y}), \mathbf{f}_j(\boldsymbol{y})||$

$$\psi_{ij}(x_i, x_j, \boldsymbol{y}) = \begin{cases} \log\left[\frac{2\lambda}{\sqrt{\lambda^2 + d^2}} \cdot h(x_i, x_j)\right] & if\,(x_i == x_j) \\ \log[h(x_i, x_j)] & otherwise \end{cases}$$

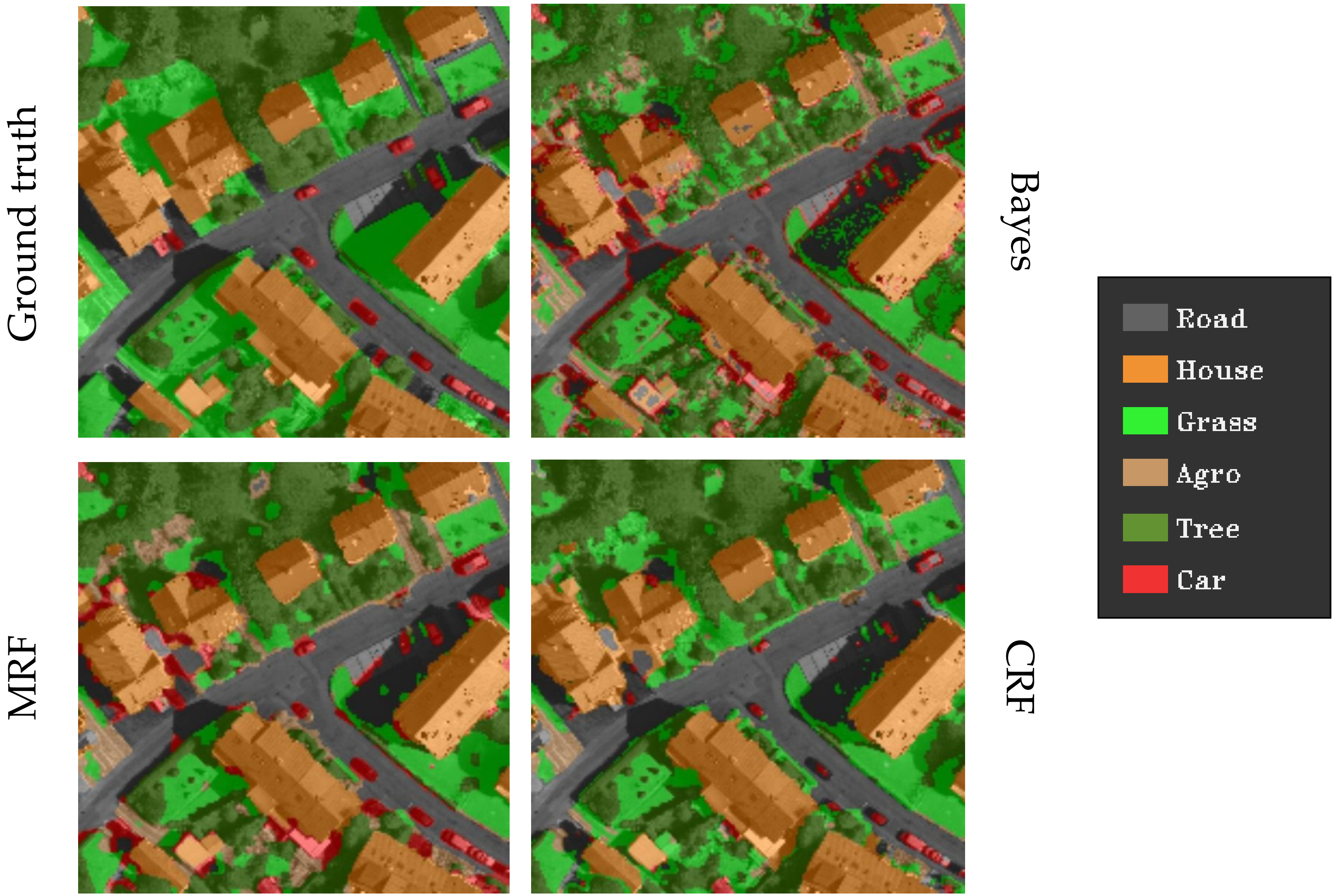
Experiments

- Cross validation on 81 colour – infrared images
- Ground sampling distance ~8cm
- 6 classes (asphalt, building, tree, grass agriculture, car)

	$NoEdge$		MRF		CRF	
	$Cm.$	$Cr.$	$Cm.$	$Cr.$	$Cm.$	$Cr.$
asp.	70.2	84.8	72.5	86.1	81.3	84.2
bld.	72.0	84.9	76.7	87.1	81.1	82.6
tr.	74.8	62.2	81.7	64.3	80.5	61.2
gr.	51.5	70.7	53.4	77.5	59.6	67.8
agr.	65.3	51.4	71.7	59.0	49.3	69.0
car	73.7	7.8	83.0	9.5	54.6	19.2
OA	**66.3**		**70.2**		**72.0**	
t_t	5.7 sec		5.7 sec		9.0 sec	
t_c	0.3 sec		13.7 sec		13.8 sec	

Completeness (Cm.), Correctness (Cr.) and overall accuracy (OA) [%] of the results and time required for training (t_t) and classification (tc).

Results



The end

- Thank you for your attention

Ready to answer your questions ☺