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Conditional Random Fields for Land Use/Land Cover Classification and Complex Region Detection

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Miyajima-Itsukushima, Hiroshima, JAPAN

Background

- Domain: Remote Sensing
- Terminology:
  - Land use: Man-made areas, e.g. urban areas
  - Land cover: Areas with natural cover, e.g. forest
  - Complex object: Areas that exhibit high intra-class variance, i.e. different colors, shapes, sizes and configurations of sub-parts, e.g. airfield

Common Strategy

- Pixel-based vs. segment-based
- Extracting discriminative features
  - NDVI for vegetation
  - NDWI for water
- Using a supervised classifier
  - k-NN
  - SVM
- What about contextual/spatial relationships?

Graphical Model Approaches

- Labels and Observations in Spatial Data are NOT independent!
  - spatially adjacent labels are often the same (Markov Random Fields and Conditional Random Fields)
  - spatially adjacent elements that have similar features often receive the same label (Conditional Random Fields)
  - spatially adjacent elements that have different features may not have correlated labels (Conditional Random Fields)

SVM vs. MRF vs. CRF

- Able to model dependencies between:

	SVM	MRF	CRF
the features of an element and its label	✓	✓	✓
the labels of adjacent elements	✗	✓	✓
the labels of adjacent elements and their features	✗	✗	✓

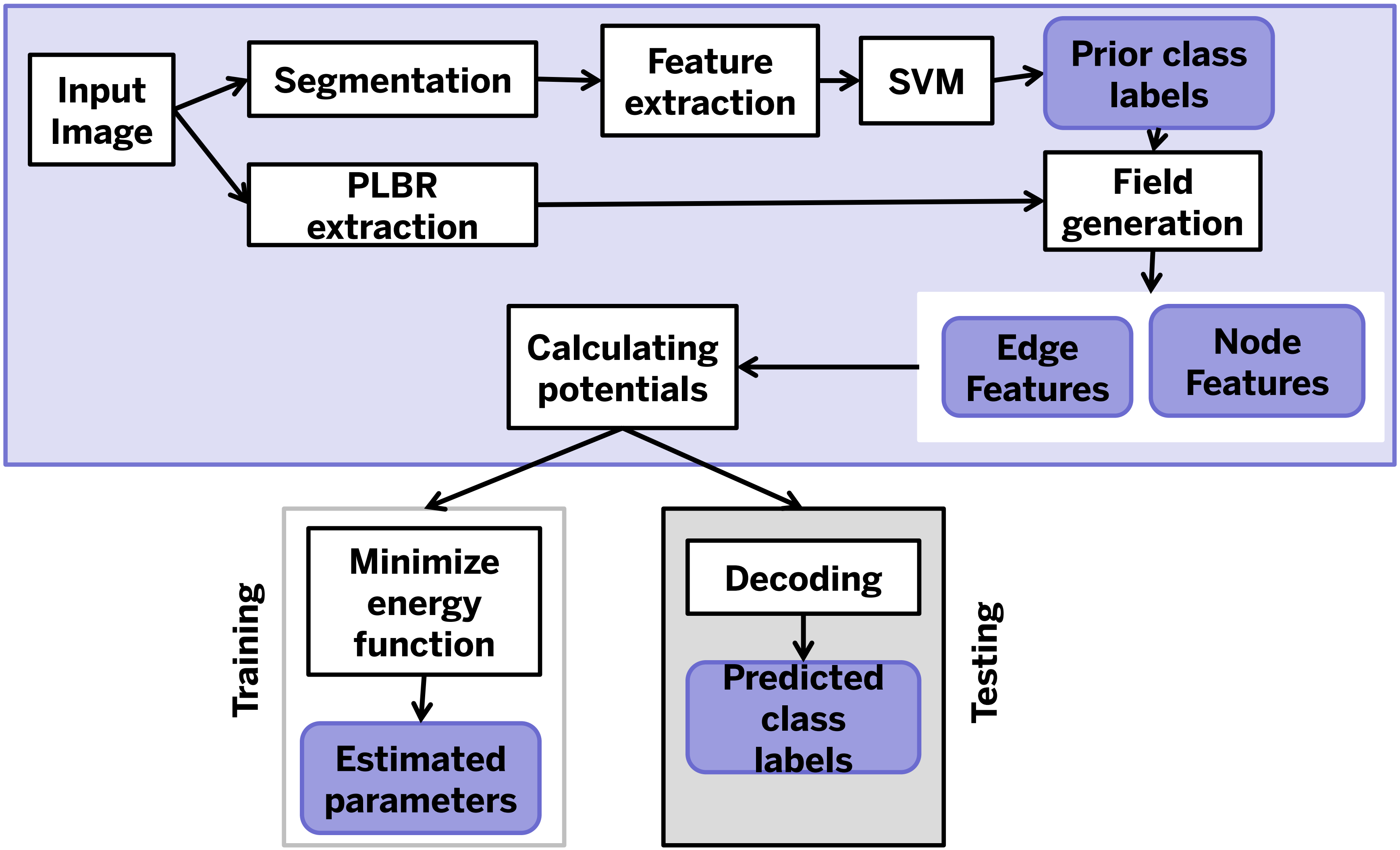
Background: *Conditional Random Fields*

- A CRF
  - A **discriminative** alternative to the traditionally generative MRFs
  - Discriminative models directly model the posterior probability of hidden variables given observations: P(Y|X)
    - No effort is required to model the prior. ☺
  - Improve the factorized form of a MRF by relaxing many of its major simplifying assumptions
  - Allows the tractable modeling of complex dependencies

Proposed Algorithm

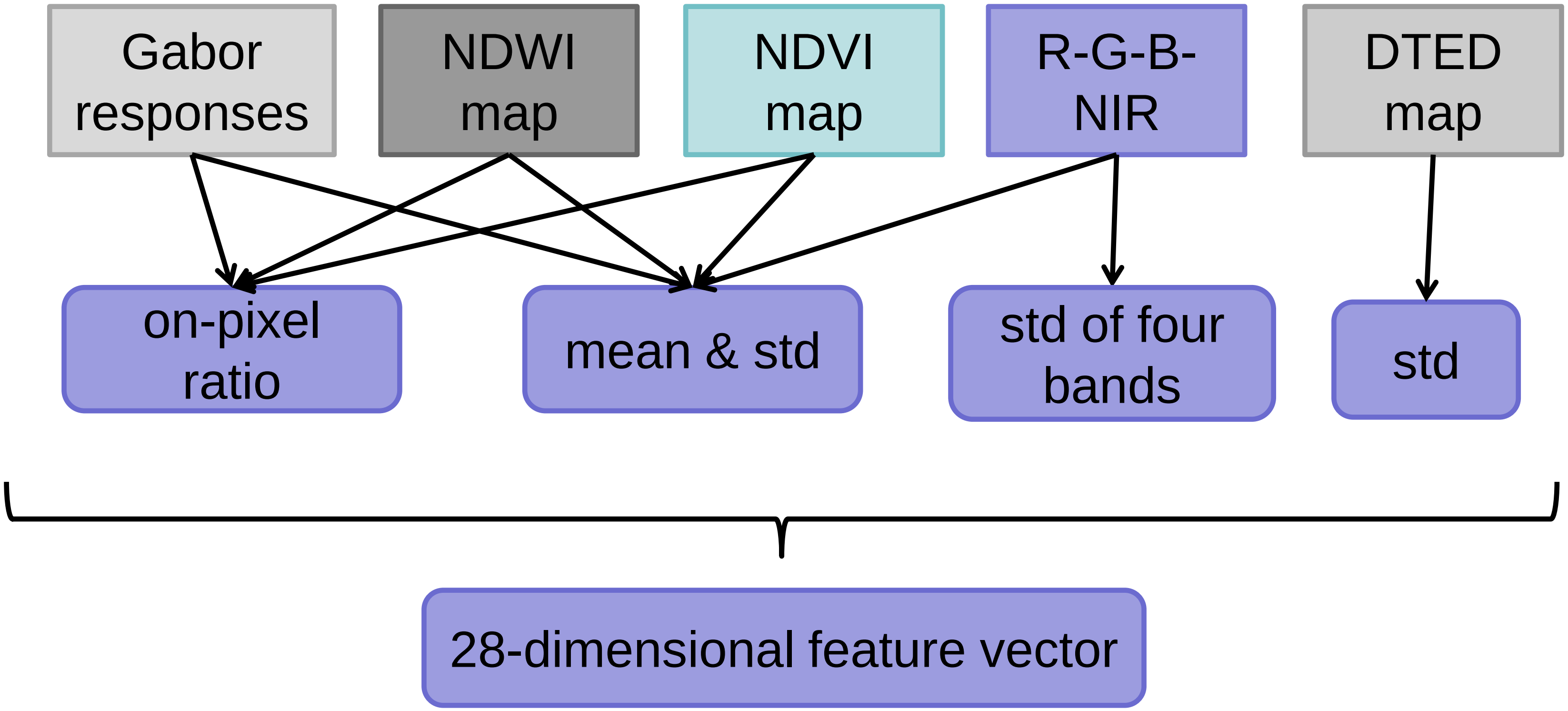
- Contextual relations between *complex object* (airfield) and its surroundings, which is characterized by Land Use/Land Cover classes, are modelled with a CRF
- Aim: identify the *complex object* by recognizing the co-occurrence pattern of all other classes in its surrounding

Flow of Proposed Algorithm



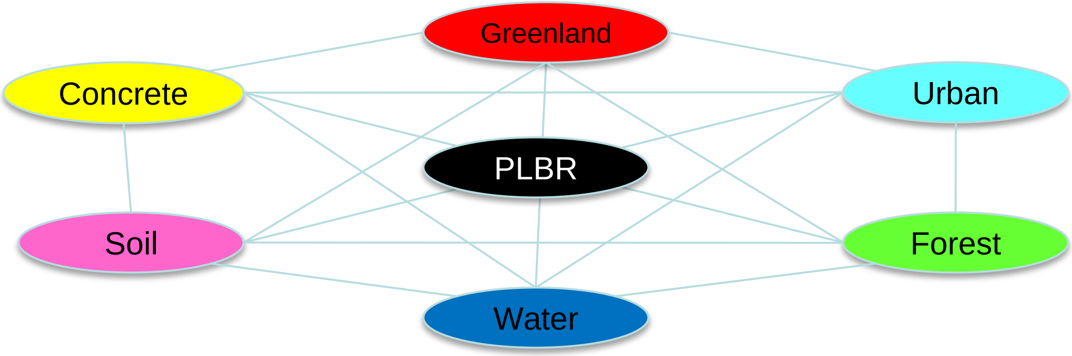
Feature Extraction

- For each segment,

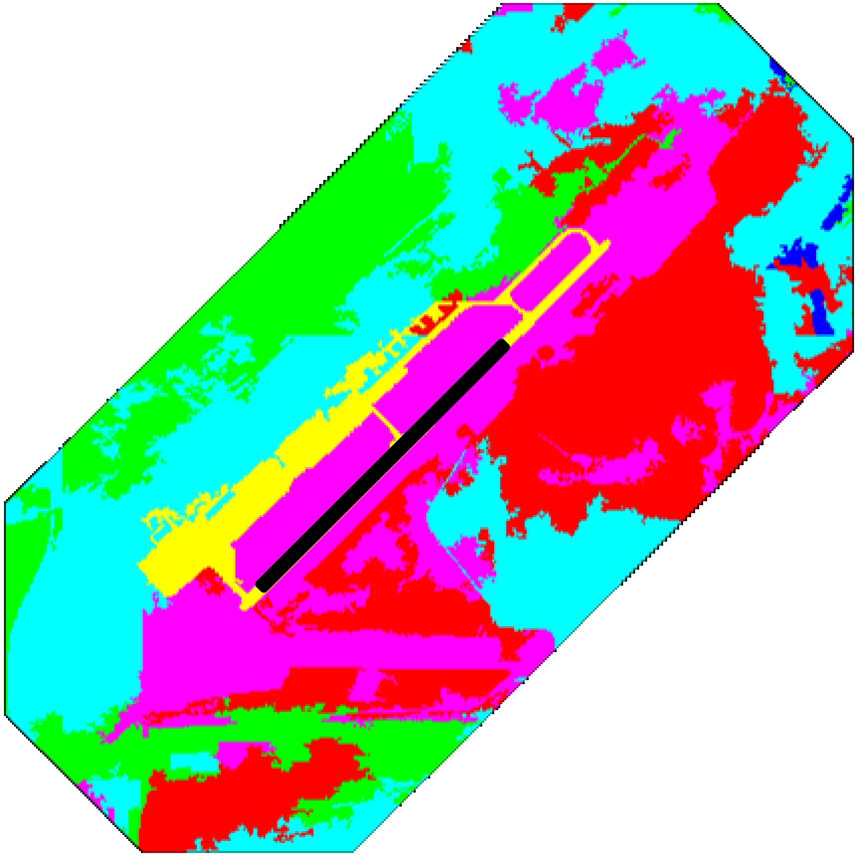


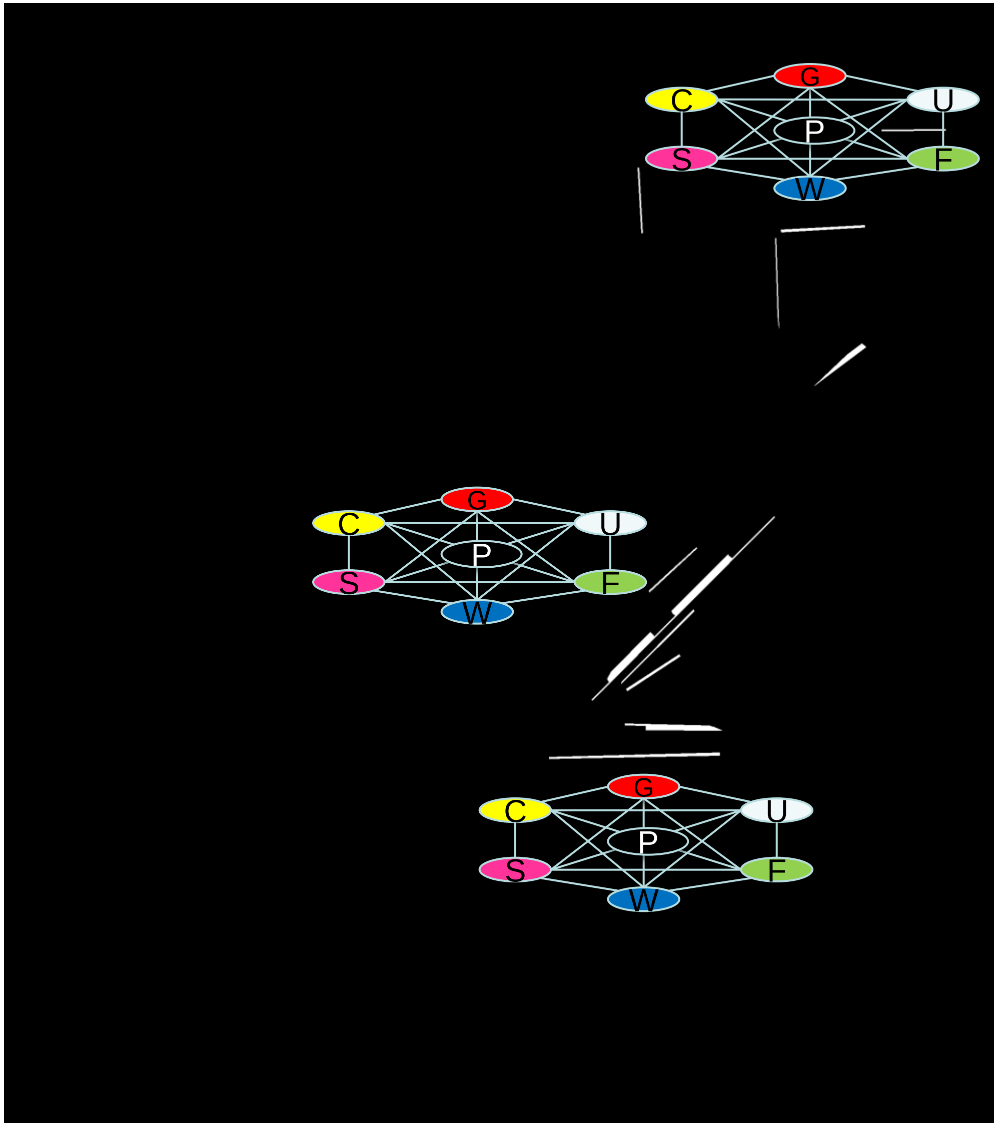
Proposed Model

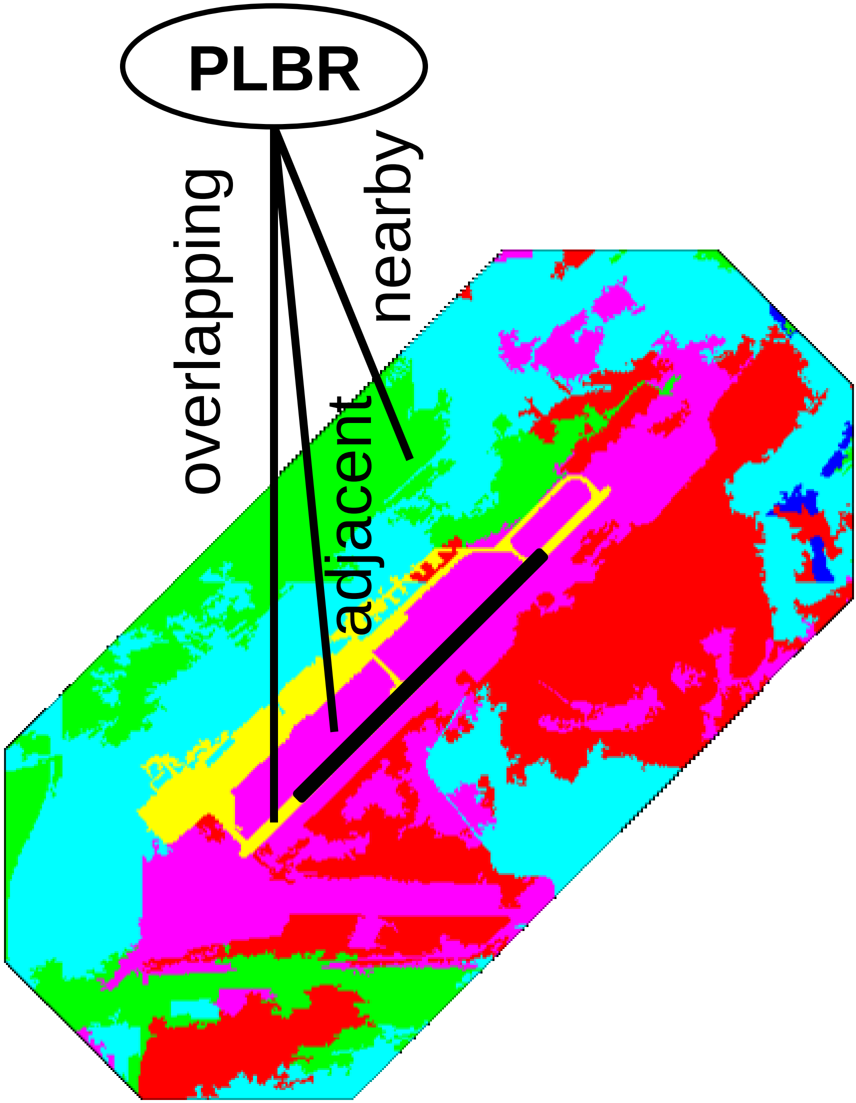
- LULC classification - ready to be used
  - Obtained by SVM with node features
- Learn spatial relations between LULC classes and complex region
  - Overlapping
  - Neighboring
  - Nearby class freqs
- Model is fixed!
  - i.e. does not change by segment size!



- Total 7+1 classes
- 3 edge features
- 28 node features







For each PLBR, we model overlapping, nearby, adjacent class frequencies as spatial features of PLBR.

Details

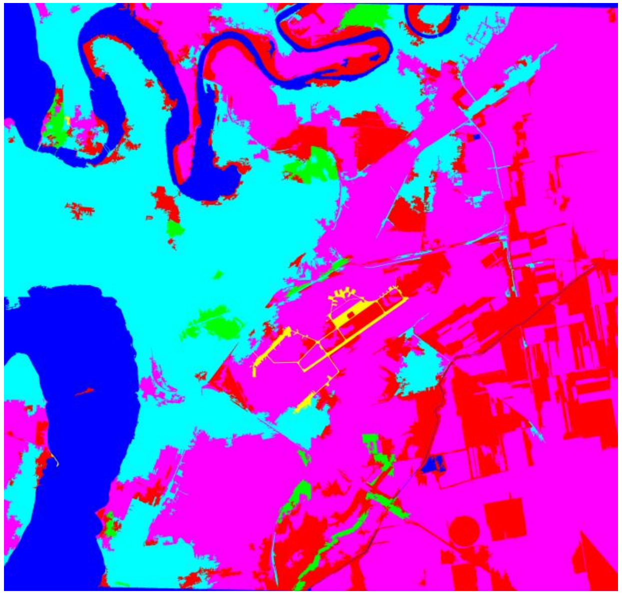
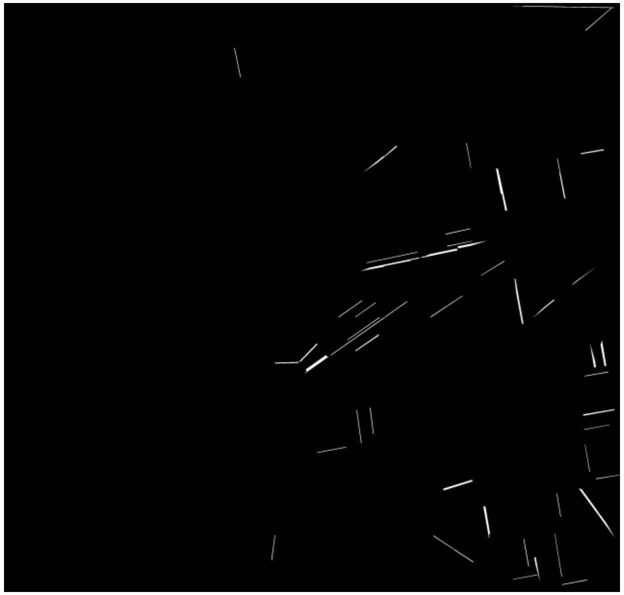
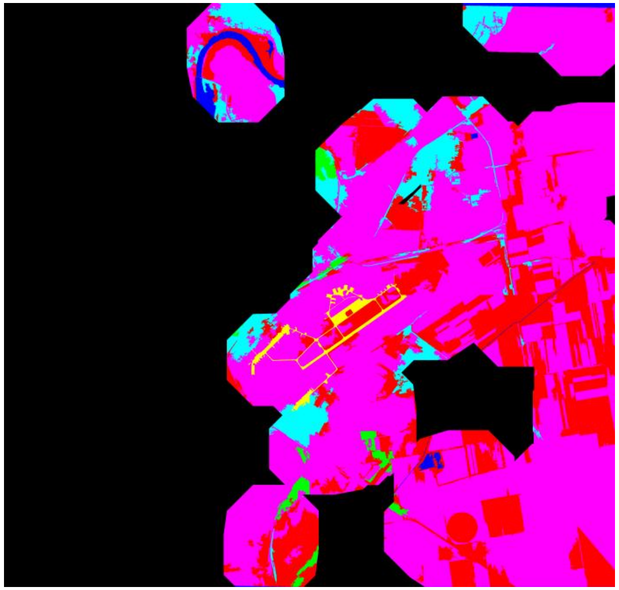
- States = 8, nodes = 7, edges = 21 (fully-connected)
- Parameter estimation (parameter sizes btw. 9688-78232)
  - L-BFGS (a quasi-Newton optimization method)
- Loss function
  - Pseudo negative log-likelihood (normalization constant is not computed)
  - Loopy belief propagation
- Decoding
  - Iterated Conditional Modes

Discussion of the Model

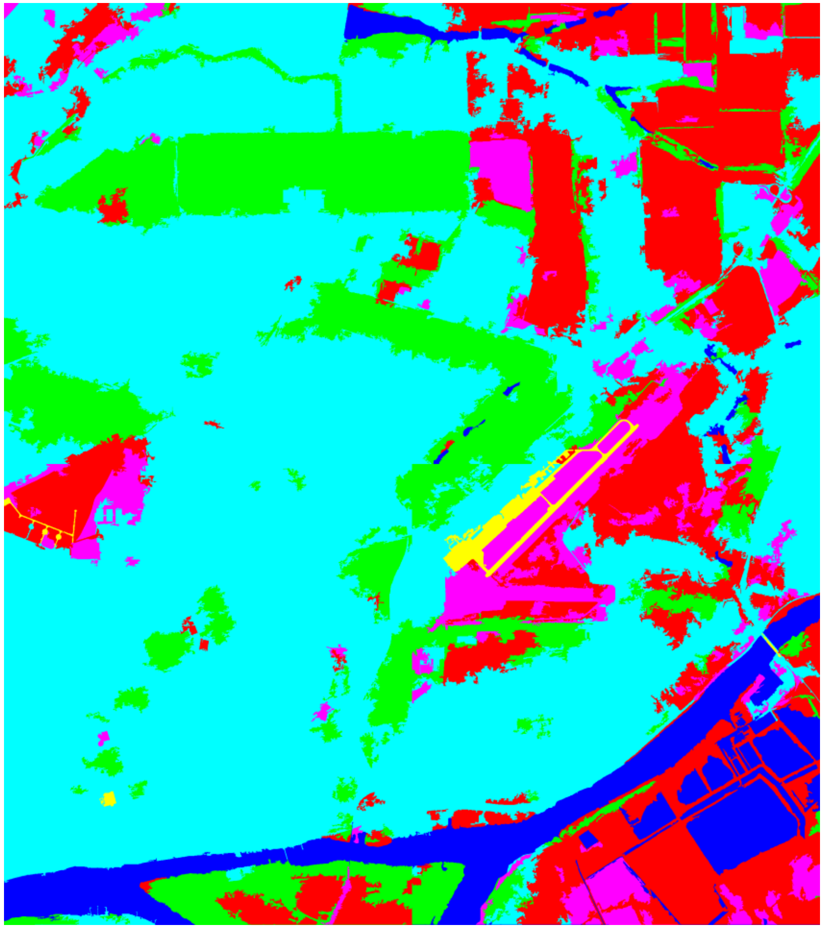
- Advantages
  - Simple
  - Fixed
  - Exact inference possible
  - Less computational burden
    - Does not treat each segment separately
- Drawbacks
  - Cannot update LULC classes (not yet)
  - Treats separate components of a class as same node (maybe an advantage btw ☺)
    - Some of which may be labelled wrongly at previous SVM step

Dataset

- 4 GEOEYE images with size of ~3800x3800 pixels
- 2 images for training (121 PLBRs)
- 2 images for testing (77 PLBRs)
- Groundtruth prepared over segmentation

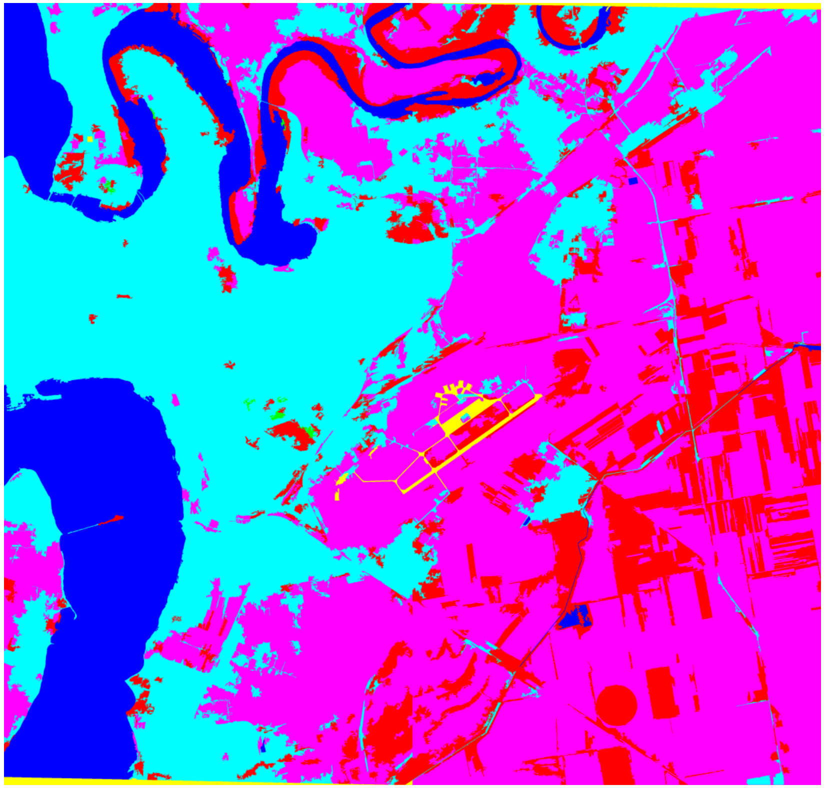
SVM results – Training Image 1



Accuracy = 91.8561% (5132/5587)

Water Urban Forest Greenland Soil Concrete

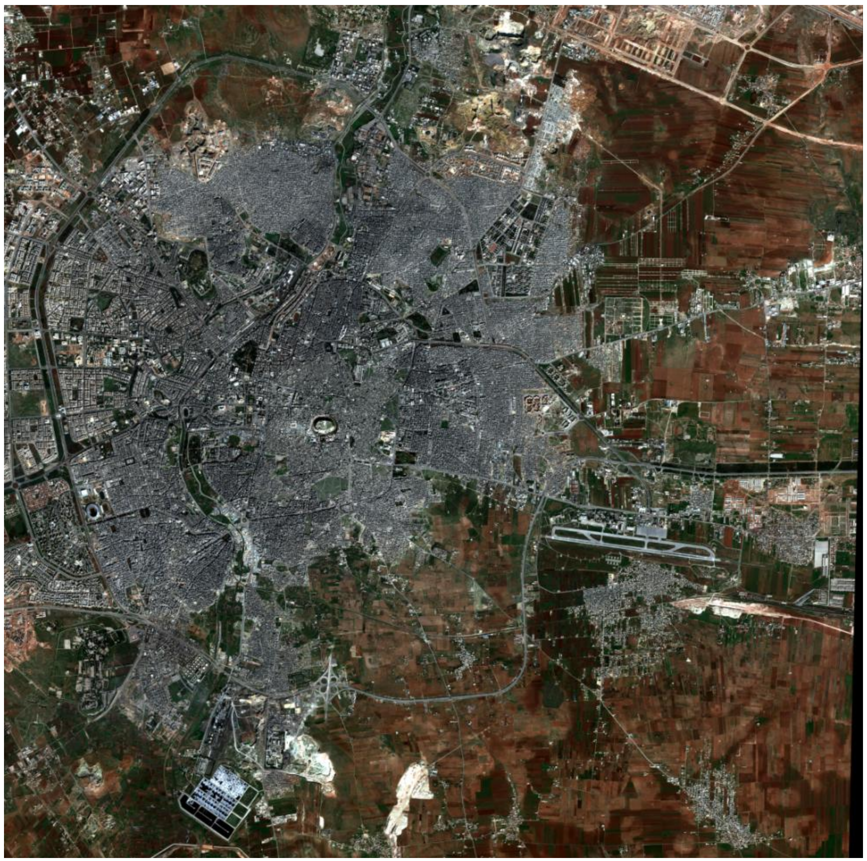
SVM results – Training Image 2

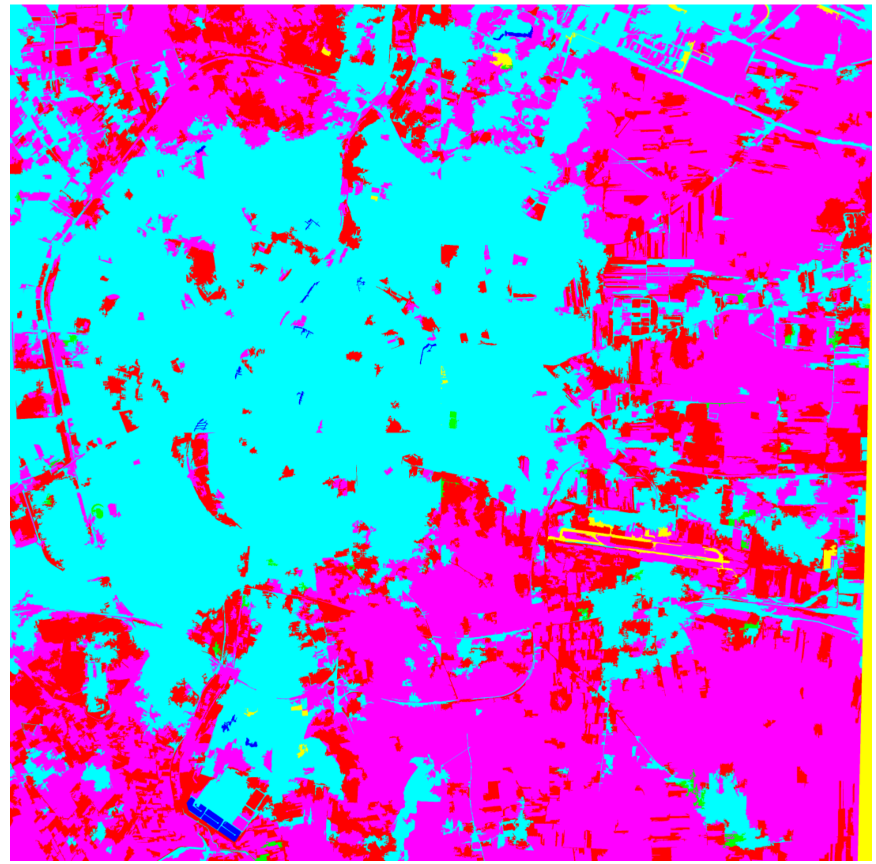


Accuracy = 82.2667% (9937/12079)

Water Urban Forest Greenland Soil Concrete

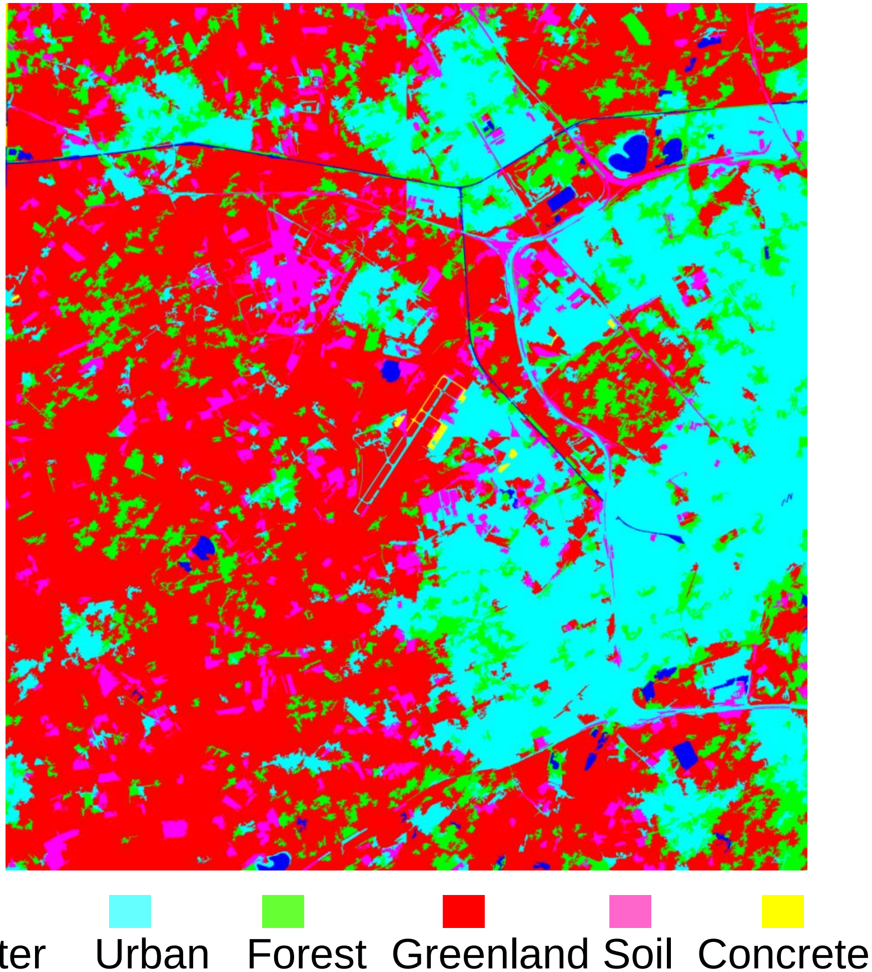
SVM results – Testing Image 1





Water Urban Forest Greenland Soil Concrete

SVM results – Testing Image 2



Results

- (PLBR on an) Airfield detection rates with the proposed CRF model:

		Edge feature selection					
		Difference of node features		Concatenation of node features		Our spatial class frequency features	
Loss function	Pseudo Negative Log-likelihood	84.61	44.90	100	20.41	92	46.94
	Loopy Belief Propogation	85.71	48.98	100	20.41	93.33	57.14
		precision	**recall**	**precision**	**recall**	**precision**	**recall**

Issues

- During training
  - In the absence of a class, label “8” fed to CRF
  - Instead, for all PLBR instances, a CRF model with varying size of nodes

- What if intermediate step is poor?

Future Work

- Exact inference and decoding
- Without the “8”th (mixed) state
  - Forcing CRF to assign a valid class label to all segments
- Star-shaped model instead of a fully-connected model
  - Better representation
  - Better fit to energy function formalization

- Intermediate step ⇨ Clustering

Questions & Answers

Thanks for listening