Cutting-Plane Training of Non-associative Markov Network for 3D Point Cloud Segmentation

GRAPHICS & MEDIA LAB VISION GROUP

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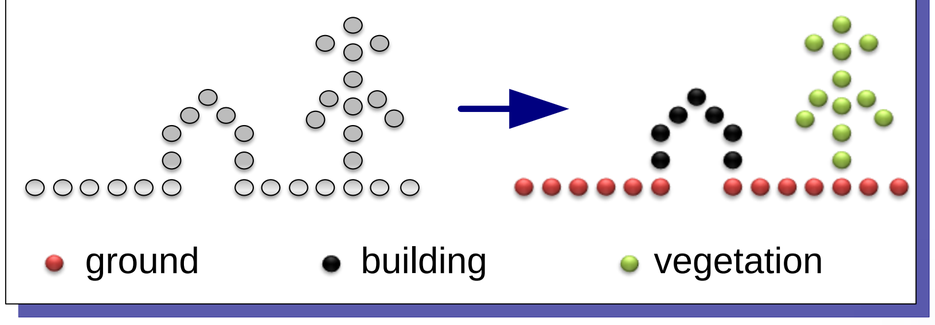
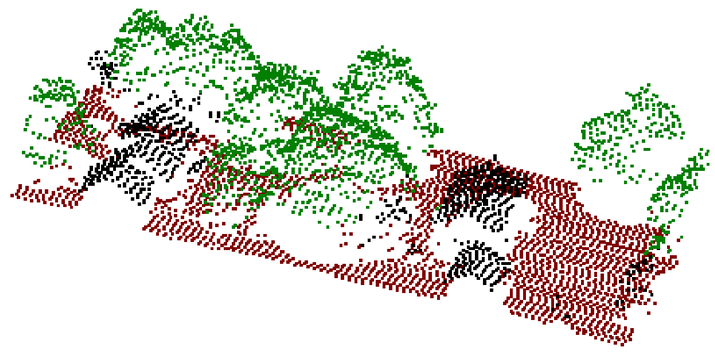
3DIMPVT 2011

Goal: Semantic segmentation

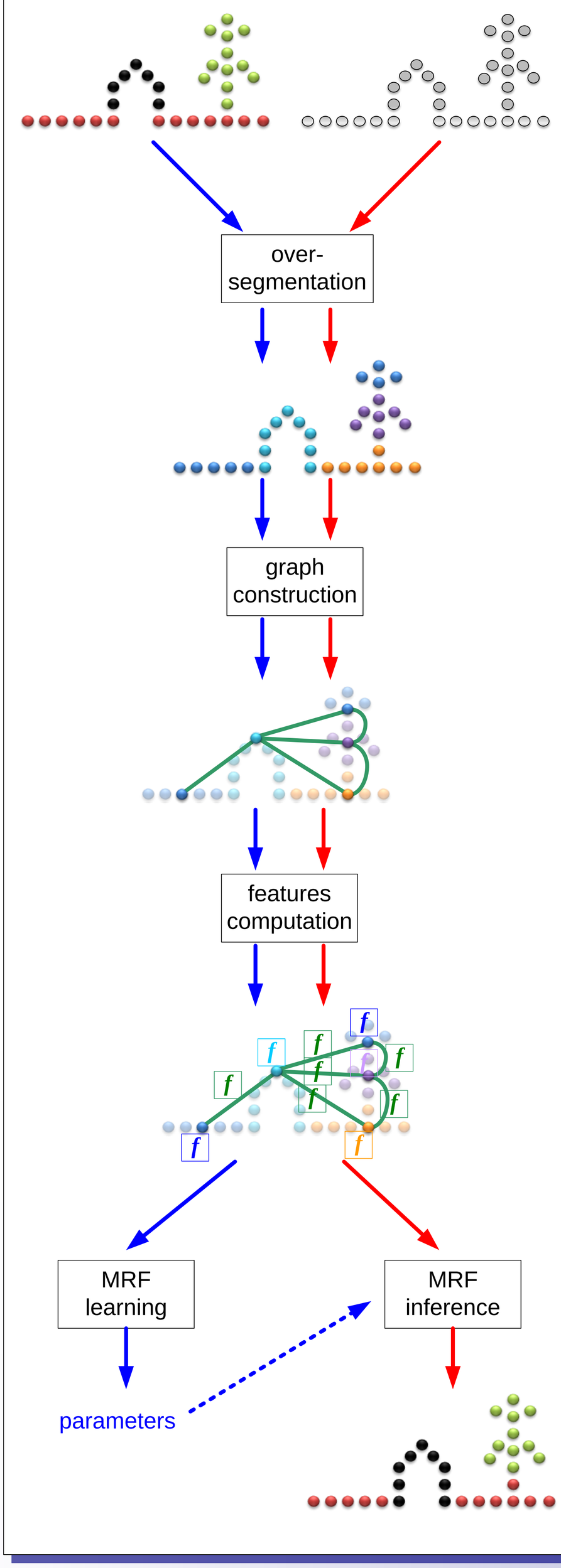


Contributions:

- principled way to train non-associative CRFs
- handles class imbalance
- non-linear model via kernelization (RBF)



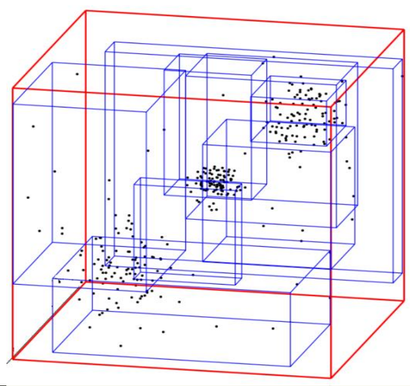
Overview



Over-segmentation

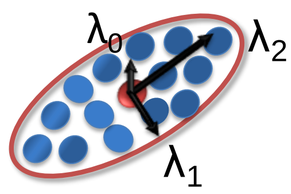
R-Tree based algorithm:

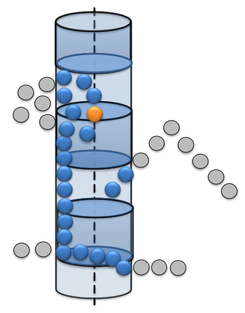
- k-means clustering for split
- tailored strategy for inserting points to get compact segments



Features

- spectral and directional features [Lalonde, 2005]
- spin images [Johnson, 1999]
- angular spin images [Endres, 2009]
- distribution of z-coordinates in infinite vertical cylinder





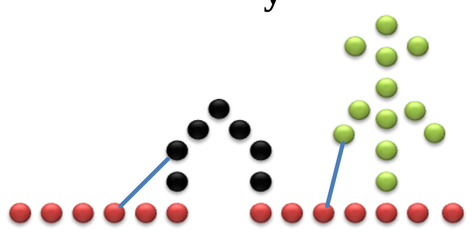
Inference: Non-associative CRFs

$$\sum_{i \in N} \phi(\mathbf{x}_i, y_i) + \sum_{(i,j) \in E} \phi(\mathbf{x}_{ij}, y_i, y_j) \to \max_{\mathbf{y}}$$

- no associative constraints [Anguelov, 2005]

$$\phi(\mathbf{x}_{ij}, y_i, y_j) \le \phi(\mathbf{x}_{ij}, k, k)$$

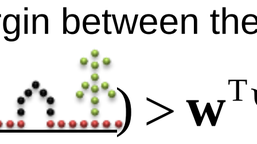
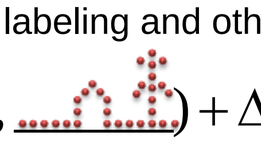
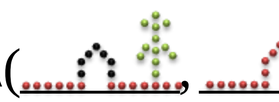
- TRW-S for inference

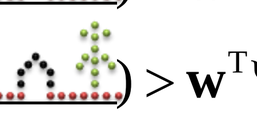
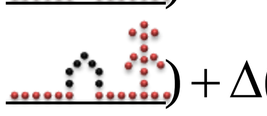
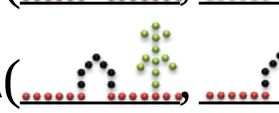


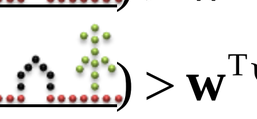
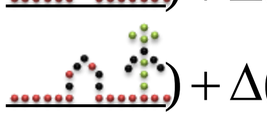
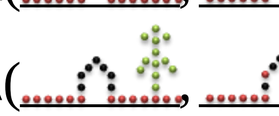
CRF Training

$$\left.\begin{aligned} \phi(\mathbf{x}_i, y_i) &= \mathbf{w}_{\mathrm{n},i}^{\mathrm{T}} \mathbf{x}_i y \\ \phi(\mathbf{x}_i, y_i, y_j) &= \mathbf{w}_{\mathrm{e},ij}^{\mathrm{T}} \mathbf{x}_{ij} y_{i,k} y_{j,l} \end{aligned}\right\} \text{ linear model } \quad \mathbf{w}^{\mathrm{T}} \Psi(\mathbf{x}, \mathbf{y}) \to \max_{\mathbf{y}}$$

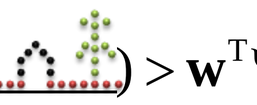
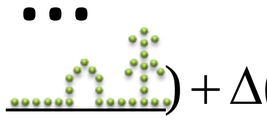
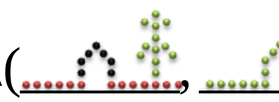
Maximize margin between the best labeling and others w.r.t. structured loss:

$\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) > \mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) + \Delta($  $) \to 19$

$\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) > \mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) + \Delta($  $) \to 12$

$\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) > \mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) + \Delta($  $) \to 7$

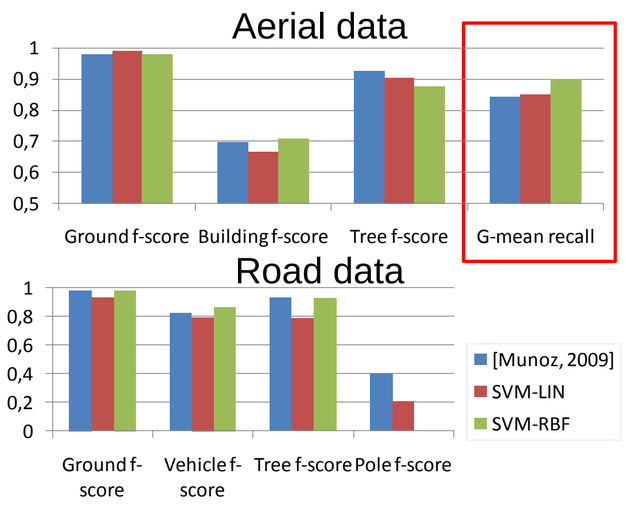
...

$\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) > \mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},$  $) + \Delta($  $) \to 13$

Exponential number of constraints

Cutting-plane scheme: iteratively add the most violated constraint [Joachims, 2009]

Results



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