GRAPHICS & MEDIA LAB
VISION GROUP

3DIM 3DPVT

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

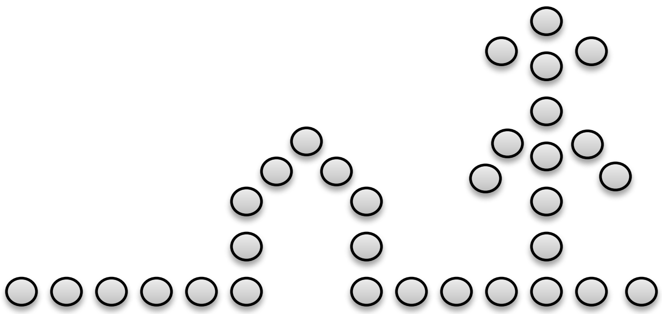
Roman Shapovalov, Alexander Velizhev

Lomonosov Moscow State University

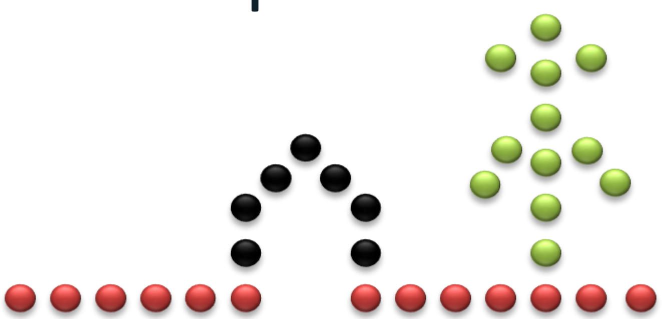
Hangzhou, May 18, 2011

Semantic segmentation of point clouds

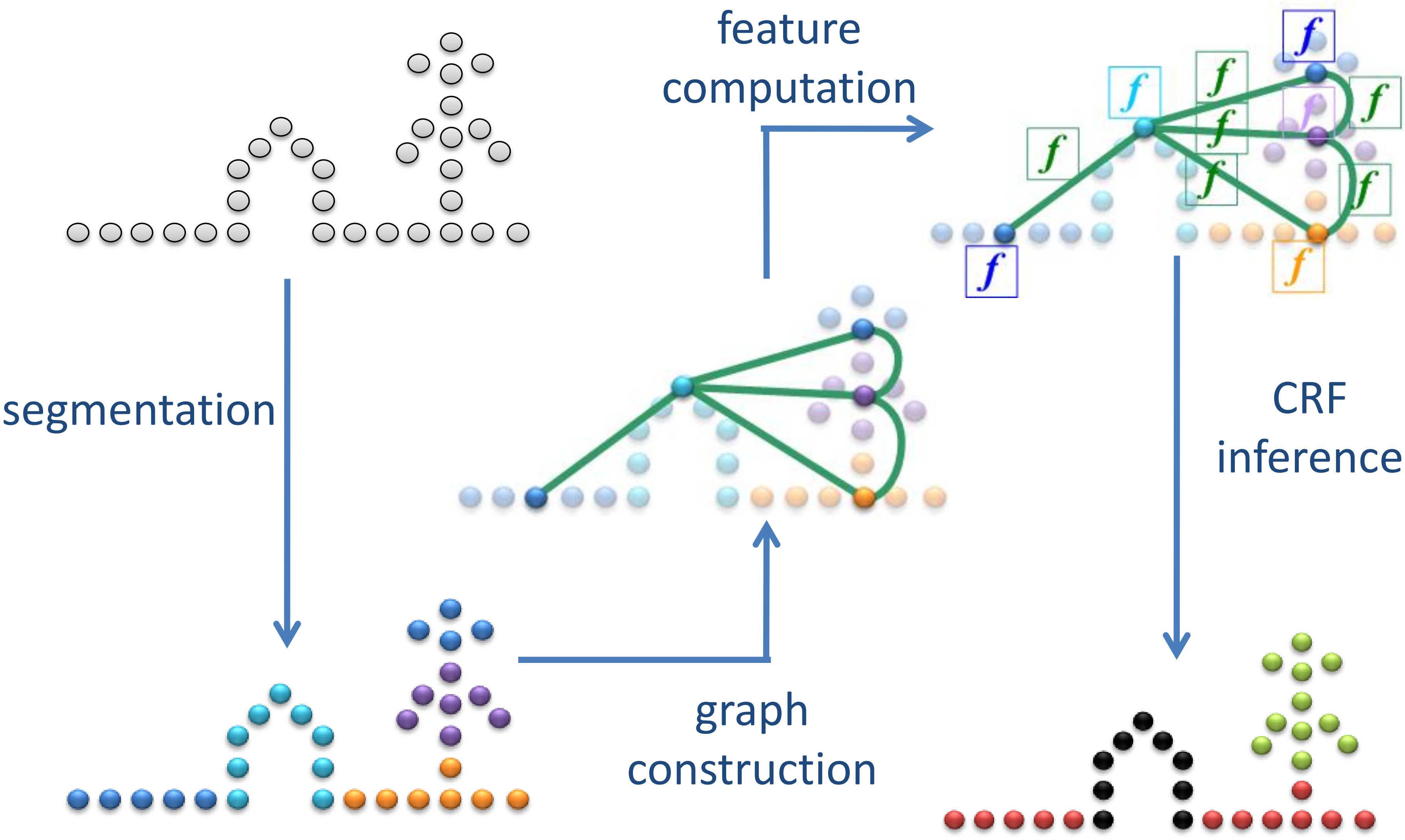
- LIDAR point cloud without color information



- Class label for each point



System workflow

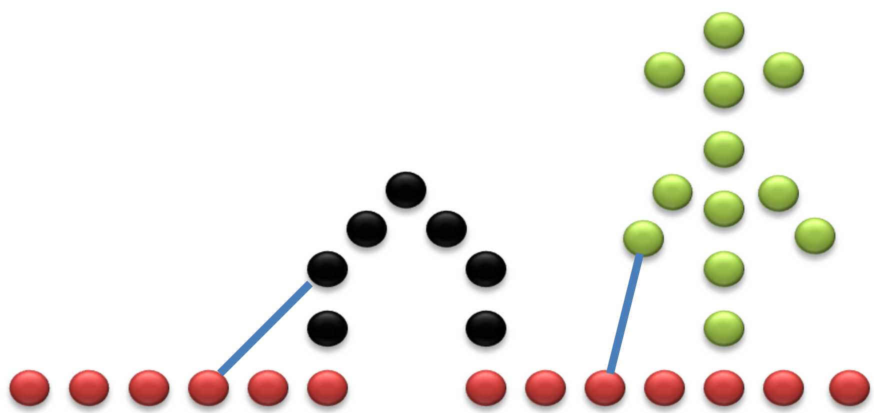


Non-associative CRF

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

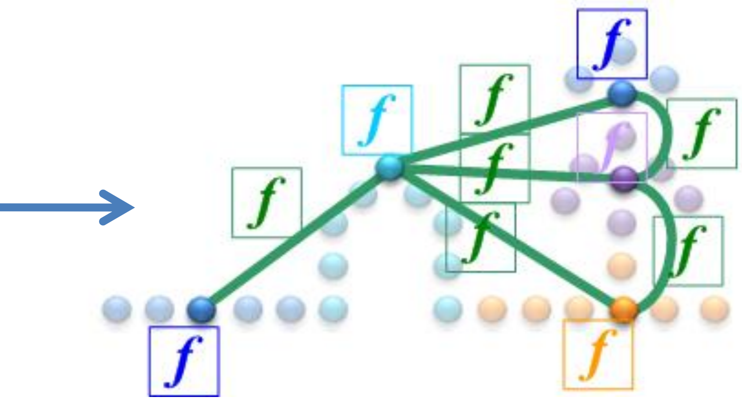
node features edge features point labels

- Associative CRF: $\phi(\mathbf{x}_{ij}, y_i, y_j) \le \phi(\mathbf{x}_{ij}, k, k)$
- Our model: no such constraints!



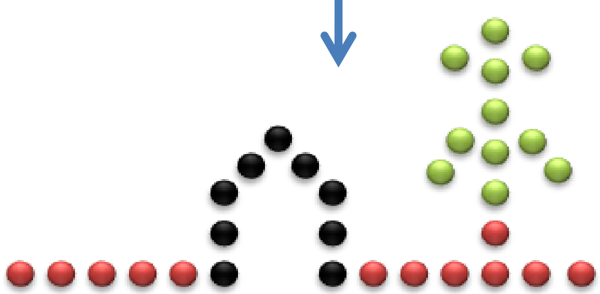
[Shapovalov et al., 2010]

CRF training



CRF
inference

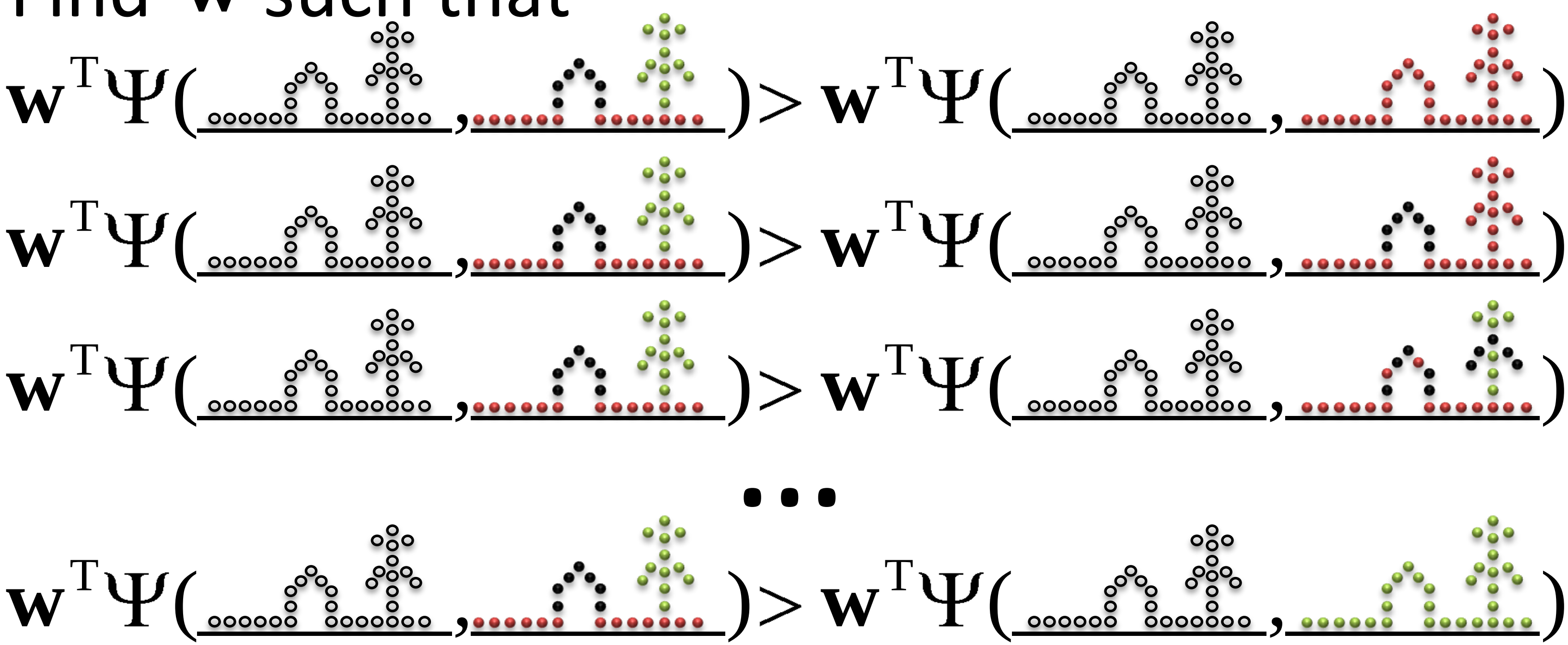
- parametric model
- parameters need to be learned!



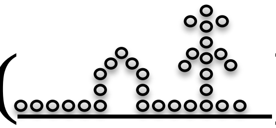
Structured learning

[Anguelov et al., 2005; and a lot more]

- Linear model:
$$\phi(\mathbf{x}_i, y_i) = \mathbf{w}_{\mathrm{n},i}^{\mathrm{T}} \mathbf{x}_i y$$
$$\phi(\mathbf{x}_i, y_i, y_j) = \mathbf{w}_{\mathrm{e},ij}^{\mathrm{T}} \mathbf{x}_{ij} y_{i,k} y_{j,l}$$
- CRF negative energy: $\mathbf{w}^{\mathrm{T}} \Psi(\mathbf{x}, \mathbf{y}) \to \max_{\mathbf{y}}$
- Find $\mathbf{w}$ such that

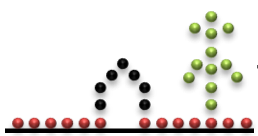
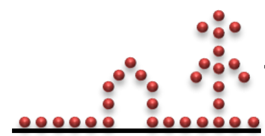
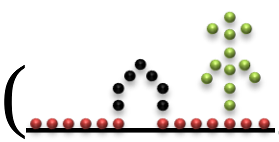
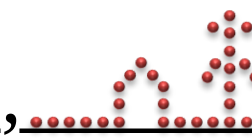


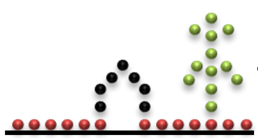
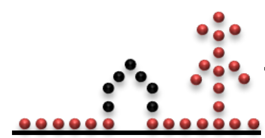
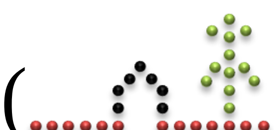
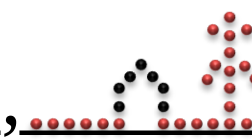
Structured loss

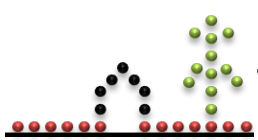
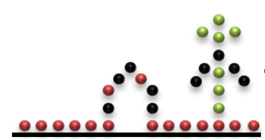
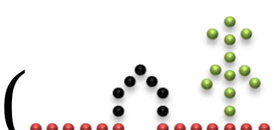
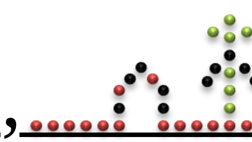
- Define $\mathbf{x} = features($$)$
- Define structured loss, for example:

$$\Delta(\mathbf{y}, \bar{\mathbf{y}}) = \sum_{i \in N} [y_i \neq \bar{y}_i]$$

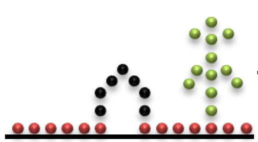
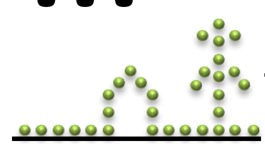
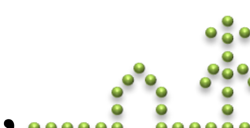
- Find $\mathbf{w}$ such that

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

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

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

…

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

Cutting-plane training

- A lot of constraints (K^n)

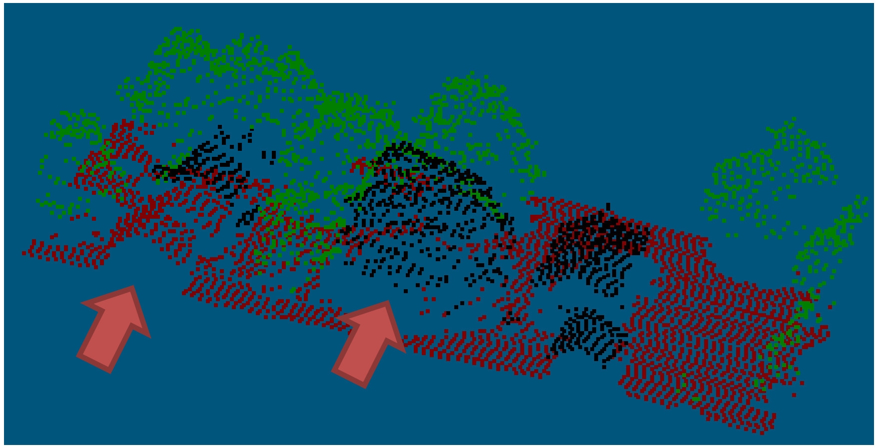
$$\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},\mathbf{y}) > \mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},\bar{\mathbf{y}}) + \Delta(\mathbf{y},\bar{\mathbf{y}}), \forall\bar{\mathbf{y}}$$

- Maintain a working set
- Add iteratively the most violated one:

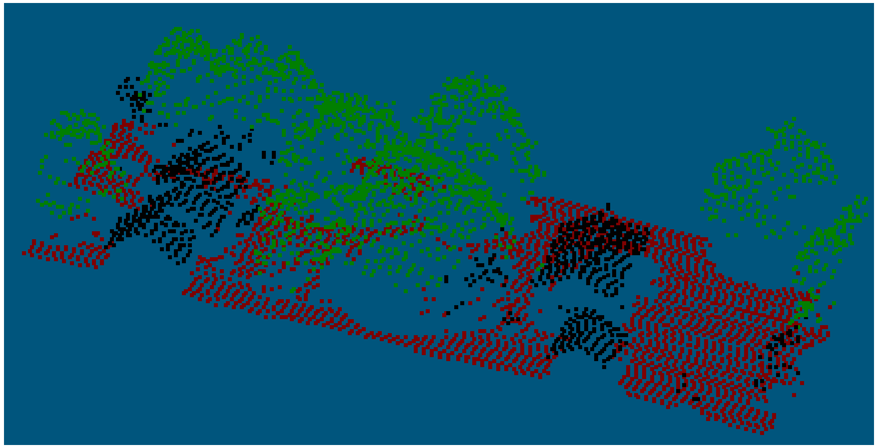
$$\bar{\mathbf{y}} = \arg\max_{\bar{\mathbf{y}}} \left[\mathbf{w}^{\mathrm{T}}\Psi(\mathbf{x},\bar{\mathbf{y}}) + \Delta(\mathbf{y},\bar{\mathbf{y}}) \right]$$

- Polynomial complexity
- SVM^{struct} implementation [Joachims, 2009]

Results

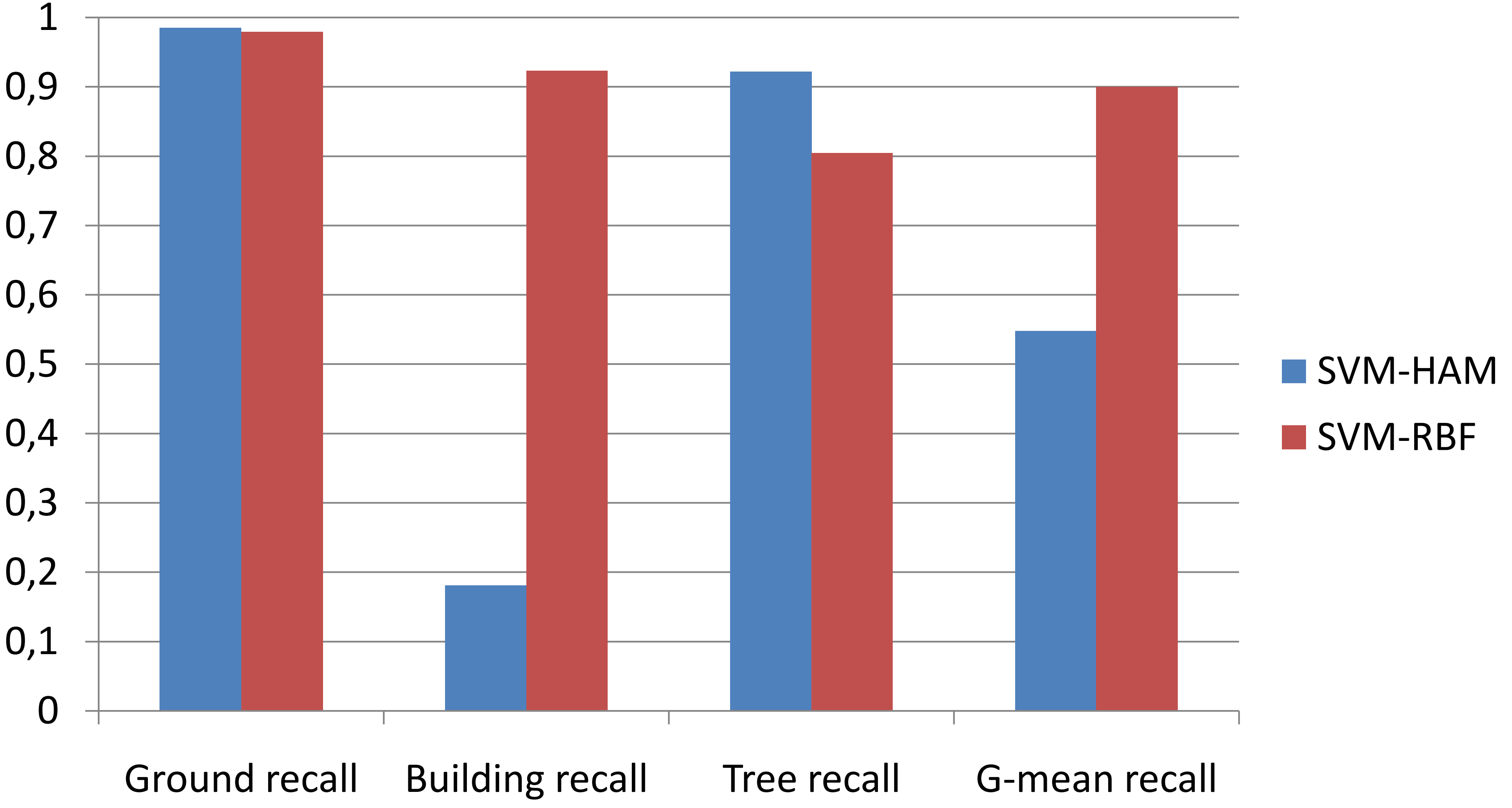


[Munoz et al., 2009]

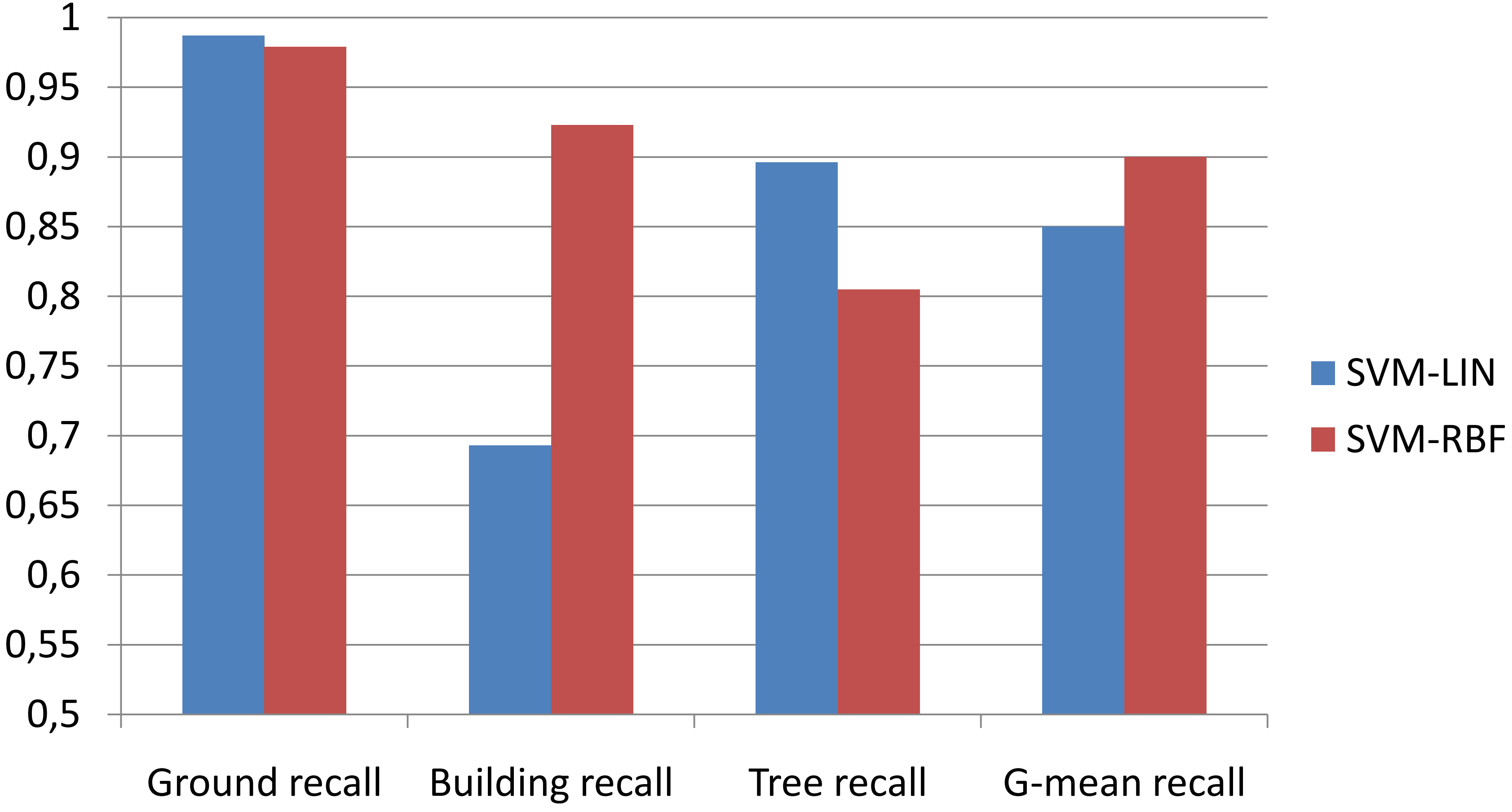


Our method

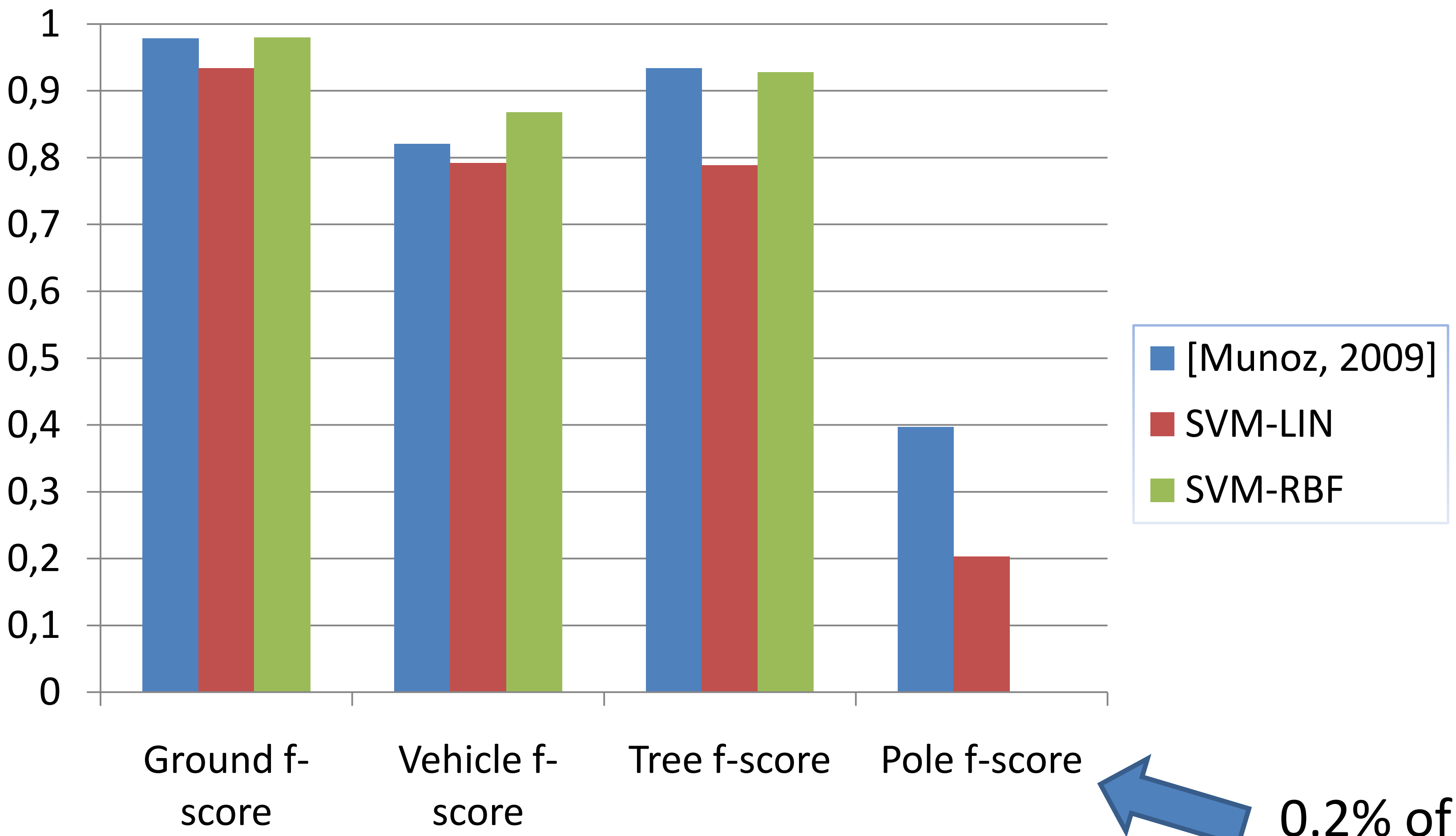
Results: balanced loss better than the Hamming one



Results: RBF better than linear



Results: fails at very small classes



0.2% of trainset

Analysis

- Advantages:
  - more flexible model
  - accounts for class imbalance
  - allows kernelization
- Disadvantages:
  - really slow (esp. with kernels)
  - learns small/underrepresented classes badly