Interactive Online Learning for Obstacle Classification on a Mobile Robot

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Online Learning

Motivation:

- Adaptation to user habits & environment
- Current methods rather simple[1]

Benefits:

- Incremental learning
- Incorporation of new classes
- Control of model complexity
- Handling of drift

Challenges:

- Stability - Plasticity

[1] R. Yang, M. Newman "Learning from a learning thermostat: Lessons for intelligent systems for the home", 2013

Contributions

1. Realization of a new interactive Learning Scenario on a Mobile Robot
   - Outdoor object recognition in a garden environment
   - Interaction via iPad
   - Recording of a challenging outdoor benchmark image dataset for learning

2. Application of prototype based learning to online scenarios
   - Extensive evalualtion of different prototype placement strategies

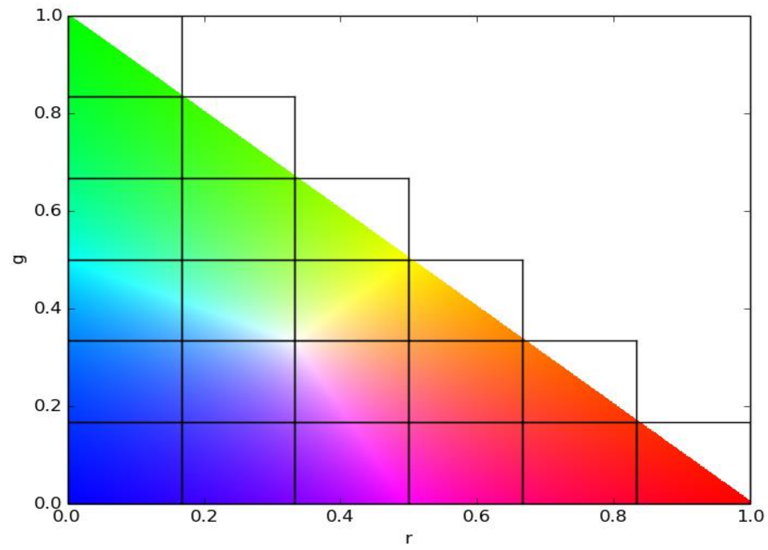
Interactive Scenario

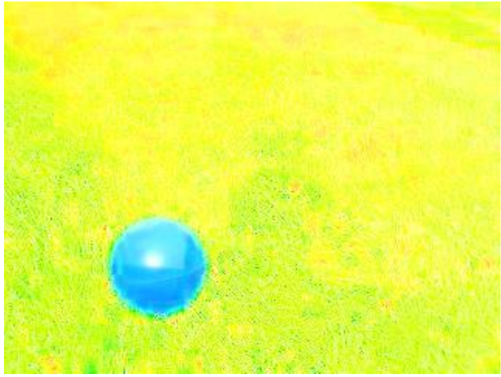
- Random exploration
- Grass-segmentation for detection
- Labeling via iPad
- Object specific actions
  - Comment
  - Drive around/over
- Confidence estimation
  - Unknown objects

Video

Feature Representation

- Color based: simple & robust
- rg-Chromaticity histogram
- Intensity invariant
- 21 dimensions
- Hist.-normalization for size invariance

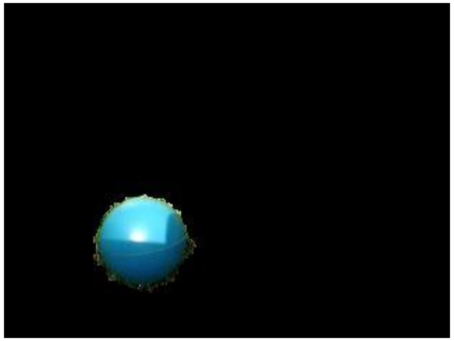




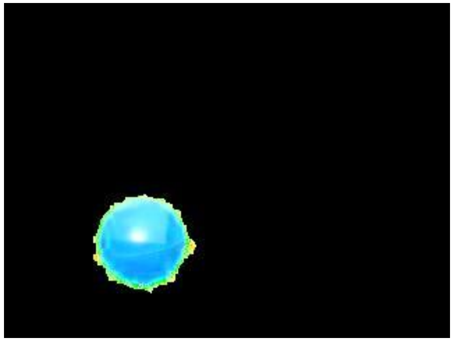
Processing Pipeline

Input

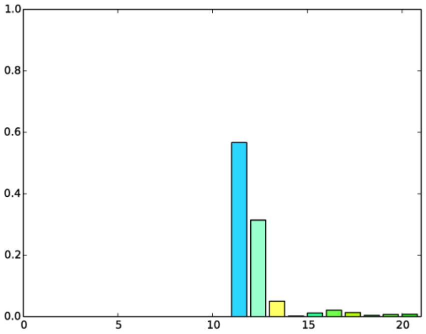
Segmentation



rg-Chromaticity



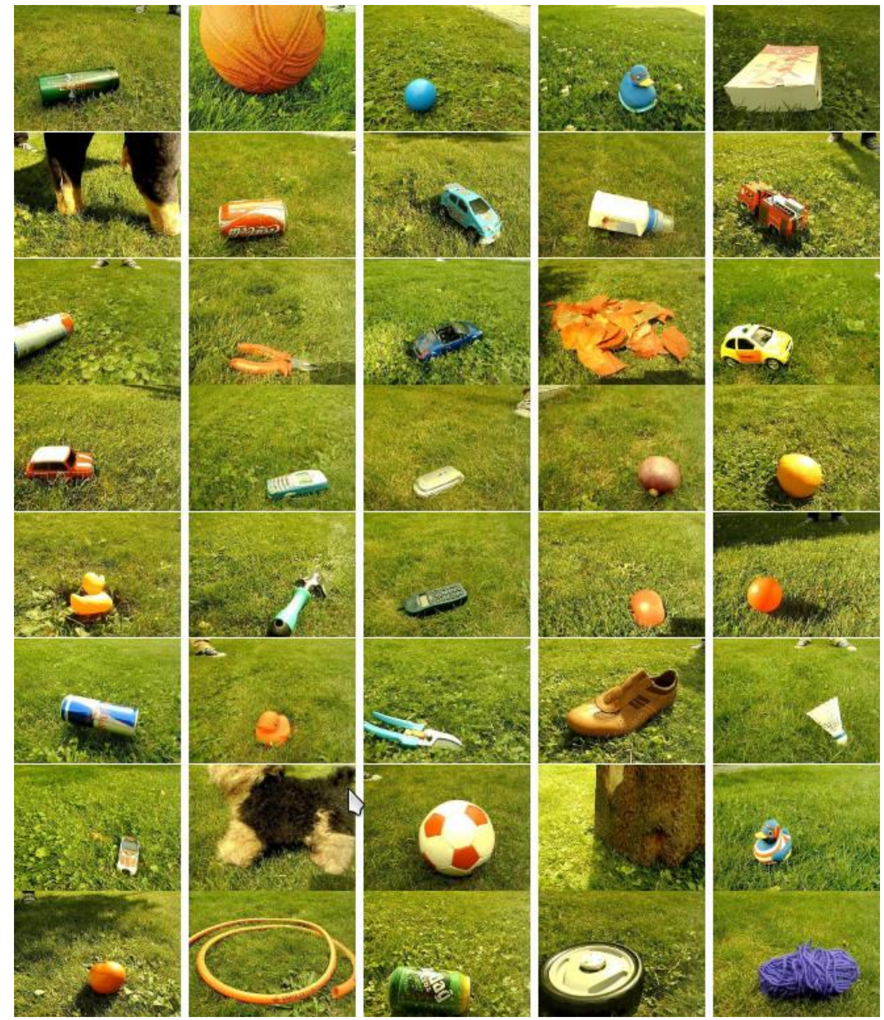
Histogram



Outdoor Benchmark Image Dataset

- 40 objects
- 5 sequences in cloudy/sunny conditions
- 10 images per sequence

Sequences

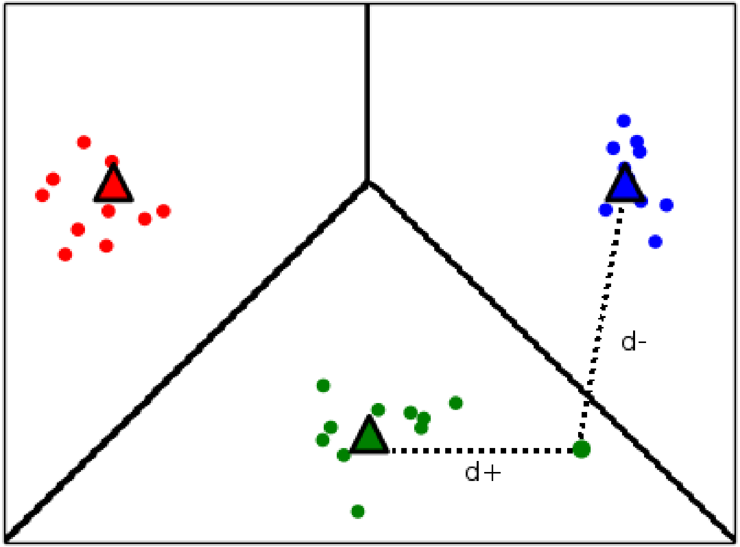


All objects

Challenges

GLVQ[1]

- Supervised, prototype–based
- $E(X) = \sum_{i=1}^{n} \Phi[(\mathrm{d}^{+}{}_{\mathrm{i}} - \mathrm{d}^{-}{}_{\mathrm{i}})/(\mathrm{d}^{+}{}_{\mathrm{i}} + \mathrm{d}^{-}{}_{\mathrm{i}})]$
- $w^{\pm} := w^{\pm} - \lambda \frac{\partial E(X)}{\partial w^{\pm}}$
- Minimized in stochastic gradient descent scheme
- Incremental version
  - Intuitive & powerful[2]
  - Complexity control

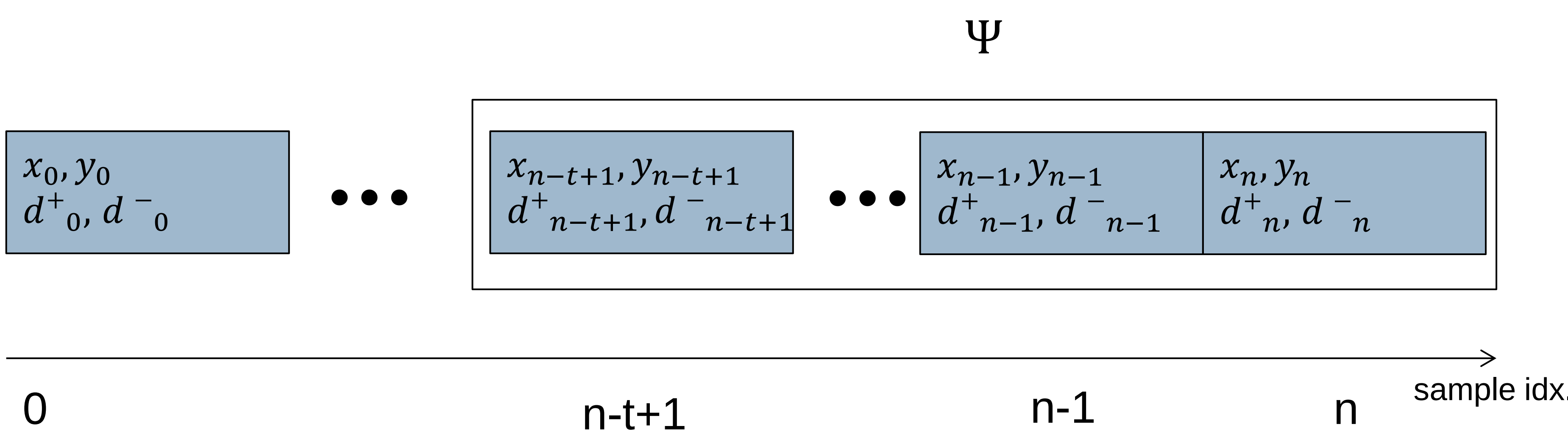


[1] A.Sato, K.Yamada "Generalized Learning Vector Quantization", 1995

[2] T. Kietzmann, S. Lange "Incremental GRLVQ: Learning relevant features for 3D object recognition", 2008

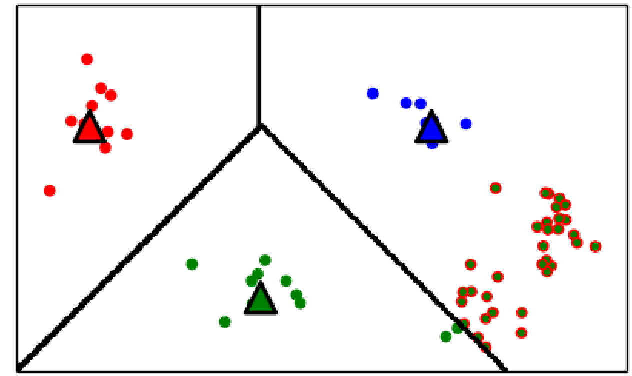
Short-term Memory

$\Psi := \langle (x_i, y_i, d^{+}_i, d^{-}_i) \mid i \in 1, \ldots, t \rangle$, window of recent t samples

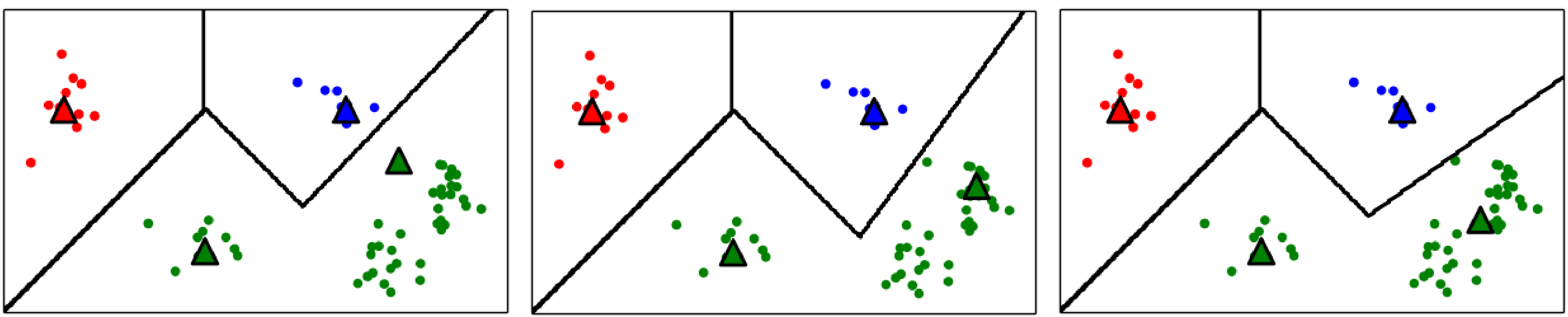


Current Placement Strategies

- Based on class-local heuristics
- Use misclassifications only



Closest[1] Cluster[2] Voronoi[3]



[1] S.Kirstein, H.Wersing “Rapid Online Learning of objects in a biologically motivated architecture“, 2005

[2] M.Grbovic, S. Vucetic “Learning Vector Quantization with adaptive prototype addition and removal“, 2009

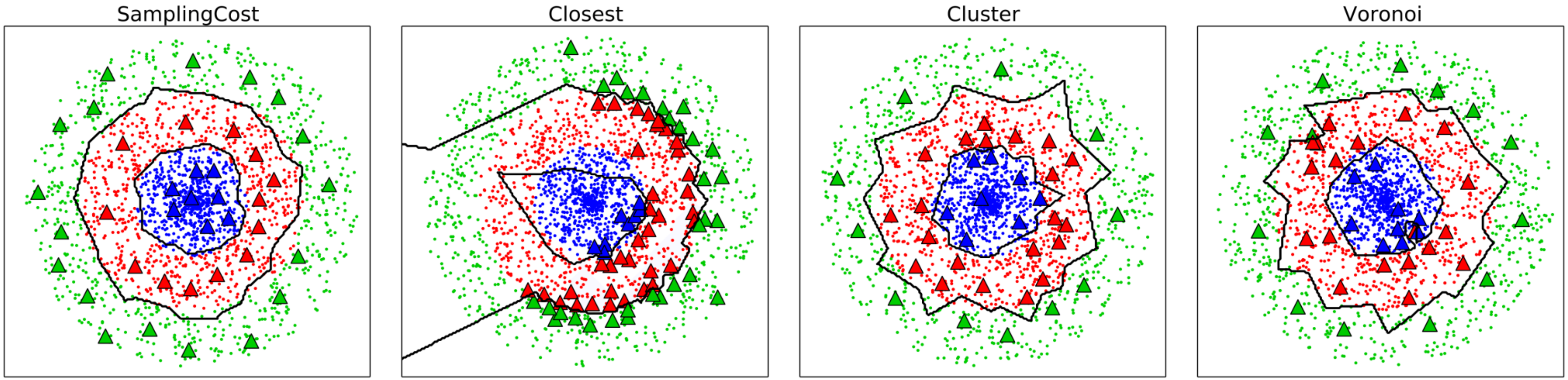
[3] S. Bermejo, J. Cabestany “A new dynamic lvq-based classifier and its application to handwritten digits“, 1998

Proposed Strategy - SamplingCost

- $\widehat{\Psi} \subseteq \Psi,\ |\widehat{\Psi}| = \hat{\mathrm{t}}$
- $\forall\ (\mathrm{x_i}, \mathrm{y_i})\ \in \widehat{\Psi}$:
  - $\widehat{\mathrm{W}_i} \coloneqq \{\mathrm{W} \cup (\mathrm{x_i}, \mathrm{y_i})\}$
  - $\dot{\Psi}_\mathrm{i} = \text{update } \Psi$
  - Calculate cost-function value $\mathrm{E}(\dot{\Psi}_\mathrm{i}, \widehat{\mathrm{W}_i})$
- Choose $\widehat{\mathrm{W}}_i$ s.t. $\mathrm{E}(\dot{\Psi}_i, \widehat{\mathrm{W}}_i)$ is minimized

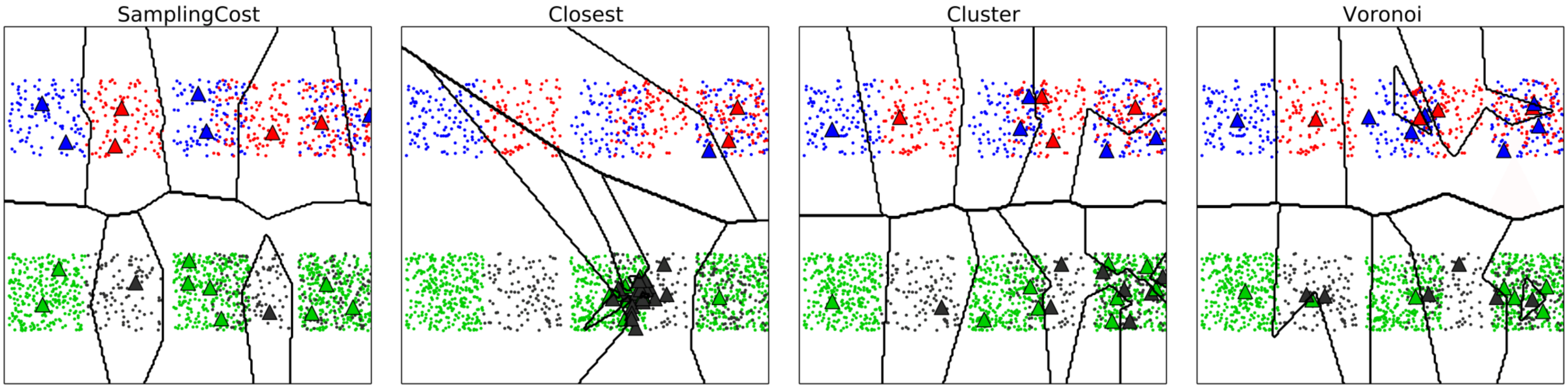
Artificial Dataset Border

Border-DS	Acc.	Nodes
SamplingCost	**93.51**	**38.2**
Closest	90.17	58.2
Cluster	91.93	42.9
Voronoi	91.71	46.4



Artificial Dataset Overlap

Overlap-DS	Acc.	Nodes
SamplingCost	**78.74**	**21.3**
Closest	65.76	29.8
Cluster	74.85	25.6
Voronoi	74.08	26.4



Outdoor Dataset

Random-order	Test acc.	Train acc.	Nodes
SamplingCost	**81.58**	85.94	**234.8**
Closest	78.03	83.23	253.4
Cluster	78.55	83.06	247.0
Voronoi	81.18	85.62	236.6

Sequence-order	Test acc.	Train acc.	Nodes
SamplingCost	**61.38**	91.04	232.0
Closest	59.58	88.04	245.8
Cluster	59.18	88.96	235.6
Voronoi	58.81	89.22	**231.3**

Sequence-order	Acc. / Nodes 500 samples	Acc. / Nodes 1500 samples	Acc. / Nodes 2800 samples
SamplingCost-GLVQ	42.9 / 116.4	58.6 / 446.2	64.3 / 948.8
SamplingCost-GMLVQ	**44.1 / 100.4**	**59.3 / 376.6**	**67.1 / 773.5**
iSVM[1]	40.6 / 363.3	57.5 / 777.0	65.2 / 1347

[1] C.P. Diehl, G. Cauwenberghs “SVM incremental learning, adaptation and optimization“, 2005

Easy/Difficult Objects

Easy

Difficult

Summary

- New interactive real-time learning scenario
- Outdoor benchmark image dataset for learning
- Proposal of cost-function based placement strategy
- SamplingCost performs superior, especially for Overlaps
- Representation not robust enough, could be extended by shape based features

Thank you for your attention!