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 et al. "Learning from a learning thermostat: Lessons for intelligent systems for the home", UbiComp 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

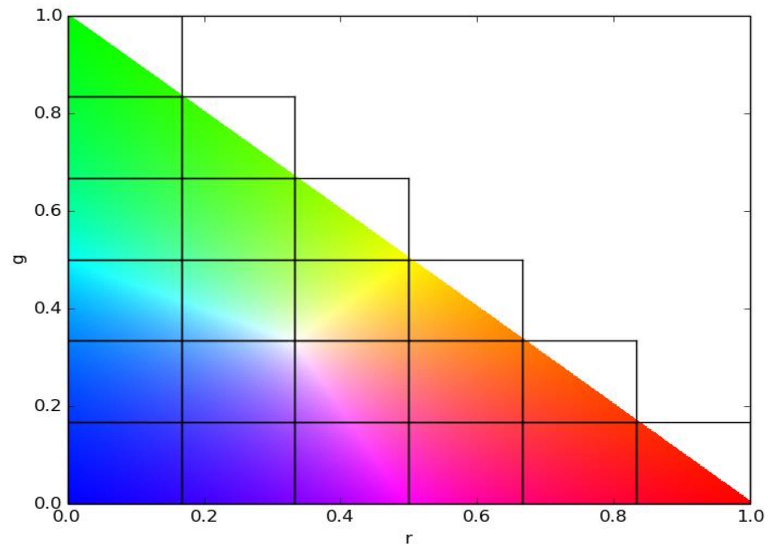
Interactive Scenario

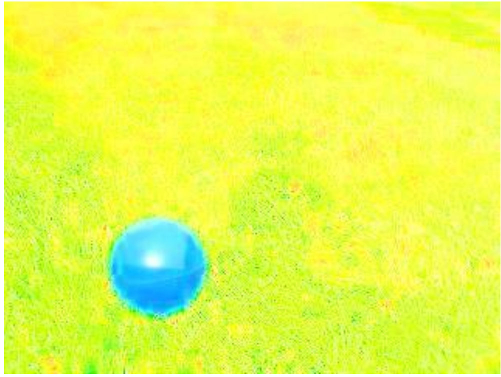
- Random exploration
- Grass-segmentation for detection
- Labeling via iPad
- Object specific actions
  - Comment
  - Drive around/over
- Confidence estimation
  - Unknown objects

Video

Feature Representation

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

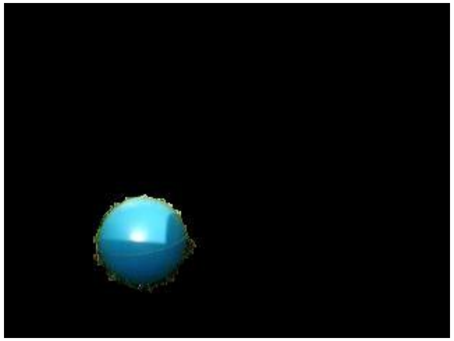




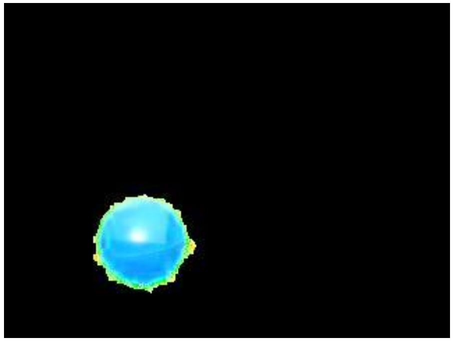
Processing Pipeline

Input

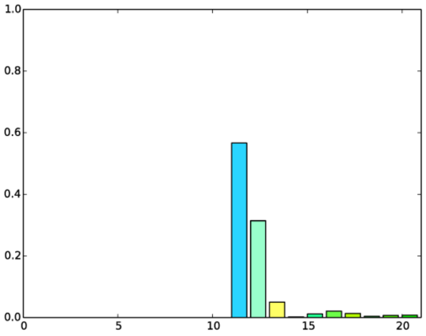
Segmentation



rg-Chromaticity



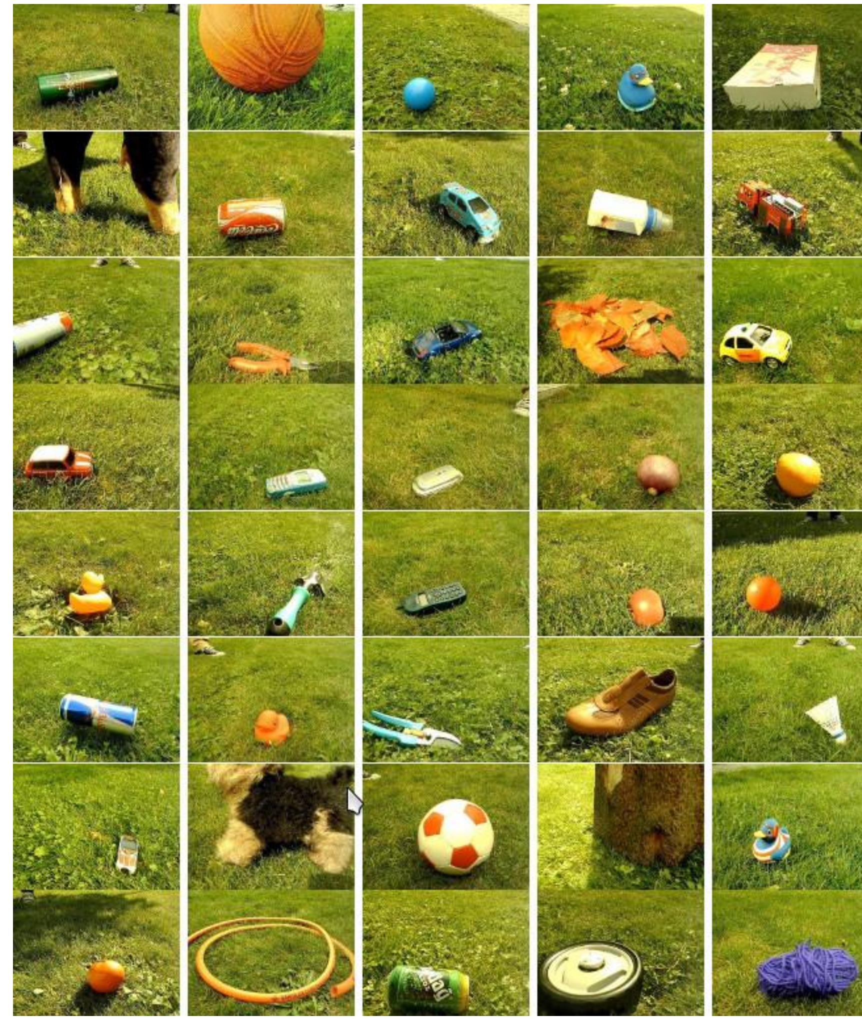
Histogram



Outdoor Benchmark Image Dataset

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

Sequences

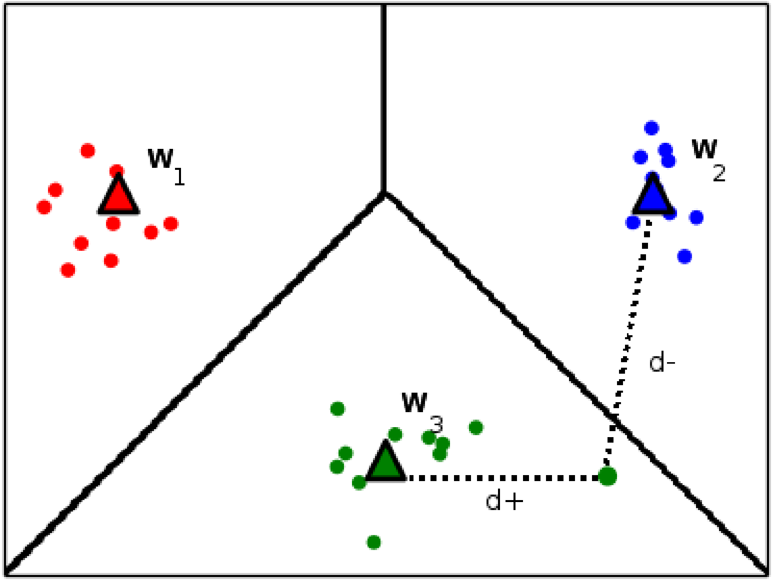


All objects

Challenges

GLVQ[1]

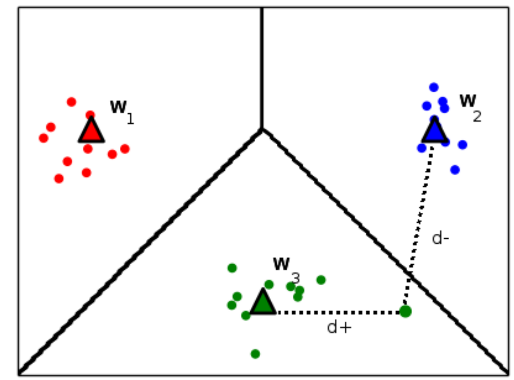
- Supervised, prototype–based
- $W = \{(w_j, l_j) | j = 1 \dots p\},\ set\ of\ prototypes$
- $E(X,W) = \sum_{i=1}^{n} \Phi[(\mathrm{d_i}^+ - \mathrm{d_i}^-)/(\mathrm{d_i}^+ + \mathrm{d_i}^-)]$
- $w^{\pm} := w^{\pm} - \lambda \frac{\partial E(X)}{\partial w^{\pm}}$
- Stochastic gradient descent
- Incremental version
  - Intuitive & powerful[2,3]
  - Complexity control

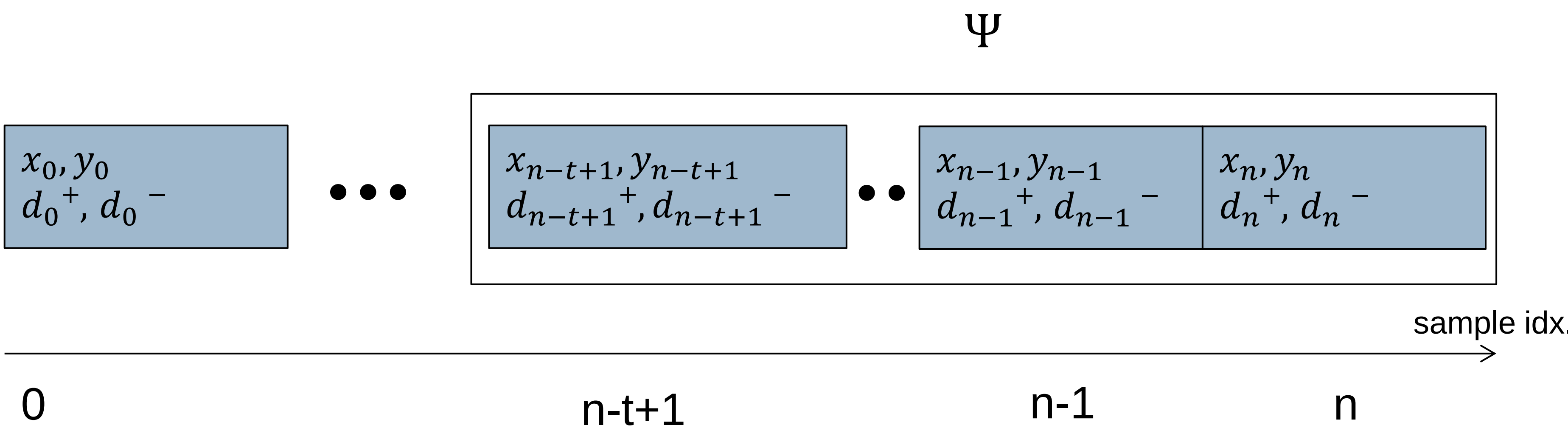


[1] A.Sato et al. "Generalized Learning Vector Quantization", NIPS 1995
[2] S.Kirstein et al. "Rapid Online Learning of objects in a biologically motivated architecture", 2005
[3] T. Kietzmann et al. "Incremental GRLVQ: Learning relevant features for 3D object recognition", Neurocomputing 2008

Short-term Memory

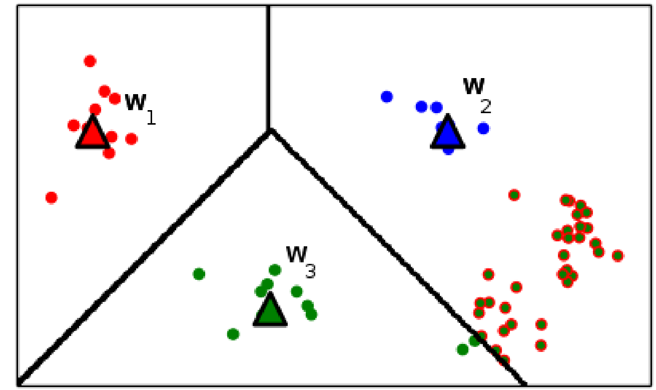
$\Psi := \langle (x_i, y_i, d_i^{+}, d_i^{-}) \mid i \in 1, \dots, t \rangle$,
window of recent t samples



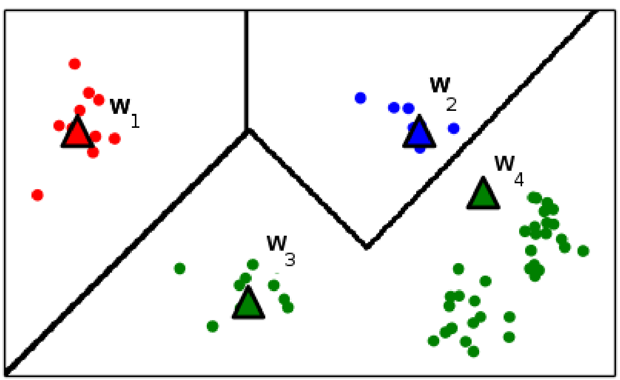


State of the Art Placement Strategies

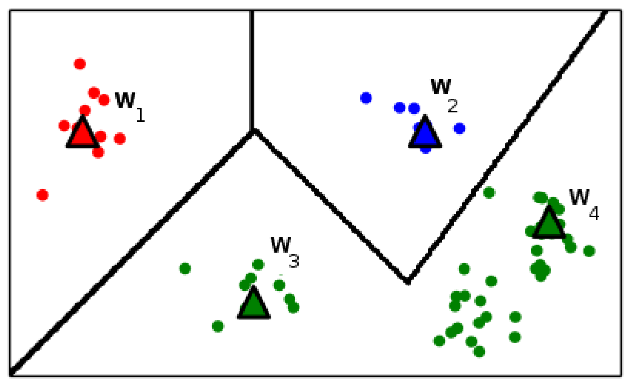
- Based on class-local heuristics
- Use misclassifications only



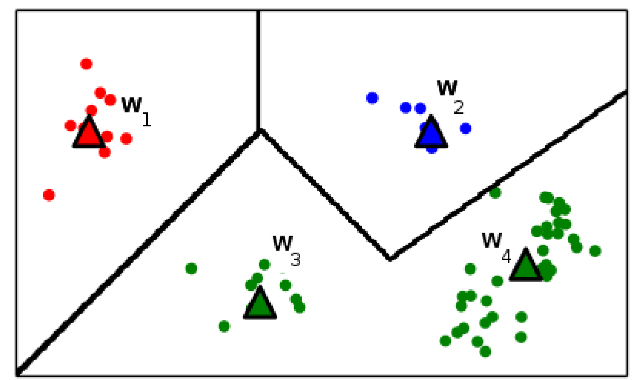
Closest[1]



Cluster[2]



Voronoi[3]



[1] S.Kirstein et al. "Rapid Online Learning of objects in a biologically motivated architecture", 2005

[2] M.Grbovic et al. "Learning Vector Quantization with adaptive prototype addition and removal", 2009

[3] S. Bermejo et al. "A new dynamic lvq-based classifier and its application to handwritten digits", 1998

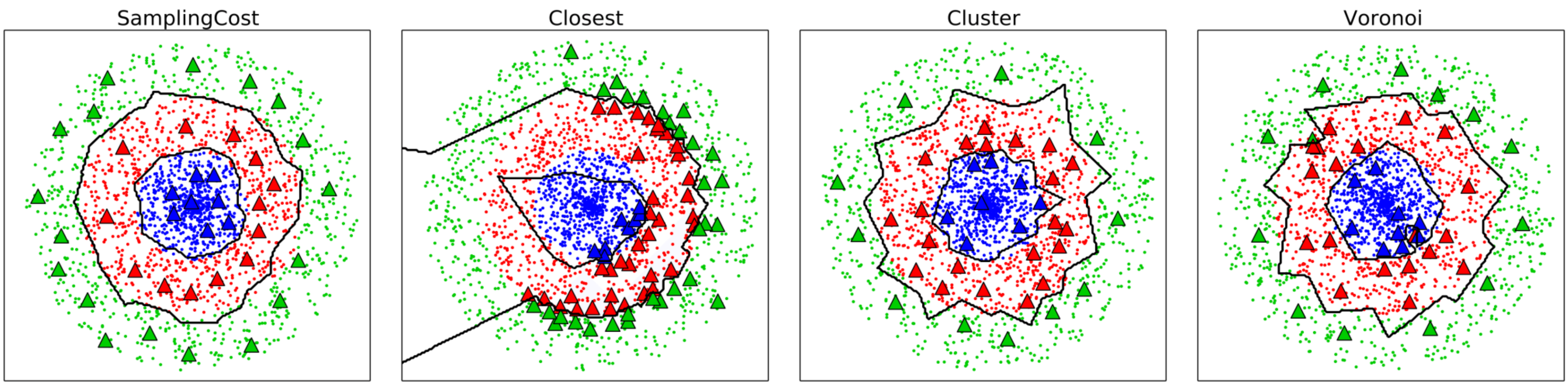
Our Strategy - SamplingCost

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

- Minimizes the cost function on the complete short-term-memory (Ψ) but evaluates only a subset of the samples ($\hat{\Psi}$) as prototypes

Artificial Dataset Border

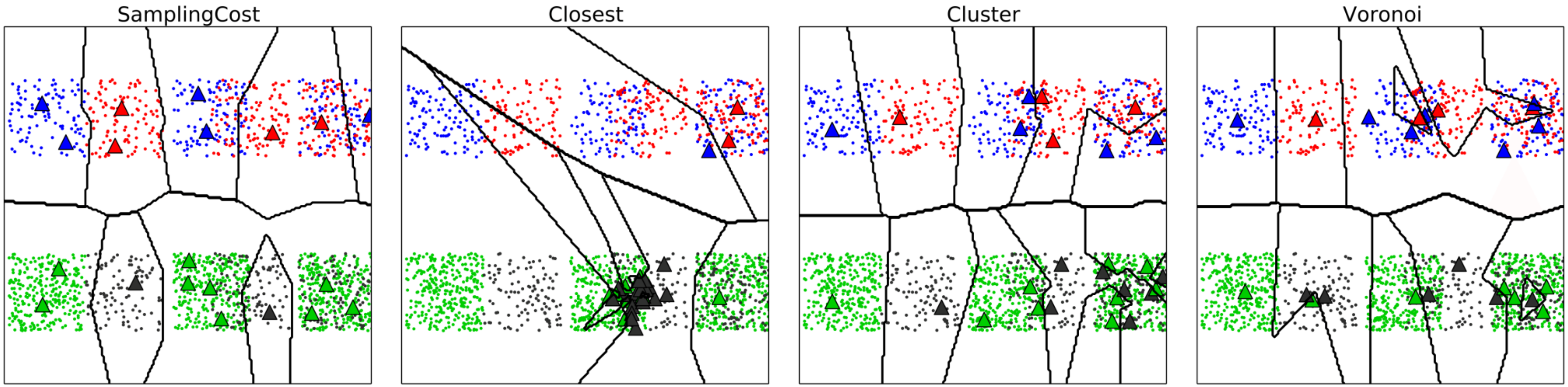
Border-DS	Acc.	|W|
SamplingCost	**93.51**	**38.2**
Closest	90.17	58.2
Cluster	91.93	42.9
Voronoi	91.71	46.4



$|W|$ = Number of prototypes

Artificial Dataset Overlap

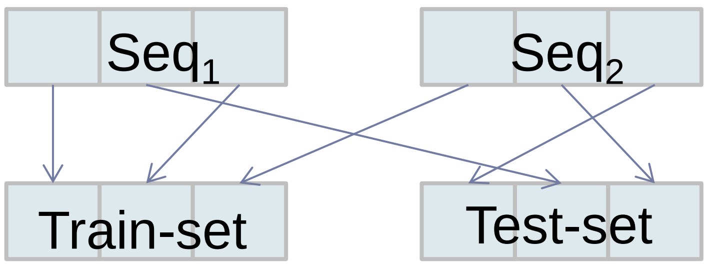
Overlap-DS	Acc.	|W|
SamplingCost	**78.74**	**21.3**
Closest	65.76	29.8
Cluster	74.85	25.6
Voronoi	74.08	26.4



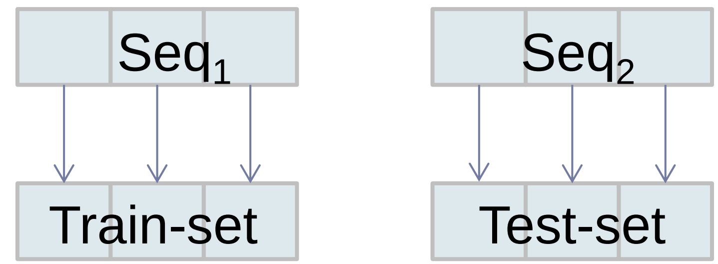
$|W|$ = Number of prototypes

Outdoor Dataset

Random-order



Sequence-order



Random-order	Test acc.	Train acc.	|W|
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.	|W|
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. / |W| 500 samples	Acc. / |W| 1500 samples	Acc. / |W| 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	40.6 / 363.3	57.5 / 777.0	65.2 / 1347

$|W| =$ Number of prototypes

[1] C.P. Diehl, G. Cauwenberghs “SVM incremental learning, adaptation and optimization“, IJCNN 2003

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[1]

[1] S. Kirstein et al. “A life-long learning vector quantization approach for interactive learning of multiple categories“, Neural Networks 2012

Thank you for your attention!