Universität Bielefeld

Cognitive Interaction Technology Center of Excellence

How to visualize a classifier?

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Quality assessment

How is the result of a classifier usually accessed?

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89.76%

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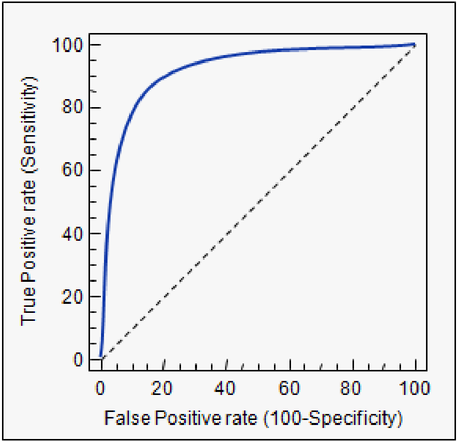

Quality assessment

How is the result of a classifier usually accessed?

Table: Confusion matrix

	1	2	3	4	5	$\sum$
1	176	10	12	7	2	207
2	1	57	11	9	3	81
3	18	25	43	31	10	127
4	1	5	23	127	4	160
5	4	3	11	26	131	175
$\sum$	200	100	100	200	150	750
class-wise accuracy of estimation in %						
	88.00	57.00	43.00	63.50	87.33	

What else could be interesting?

More information about the result:

- Which samples near to the decision boundary?
- Which samples are classified incorrectly and “how much”?
- How smooth is the decision boundary?
- How are the modes of the classes structured?
- How are errors distributed?

Where is the Difficulty?

Class borders are

- Often non linear
- Often not given in an explicit functional form (e.g. SVM)
- High-dimensional $\rightarrow$ non feasible for visualization

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   DR method (should map relative positions of classes faithfully)

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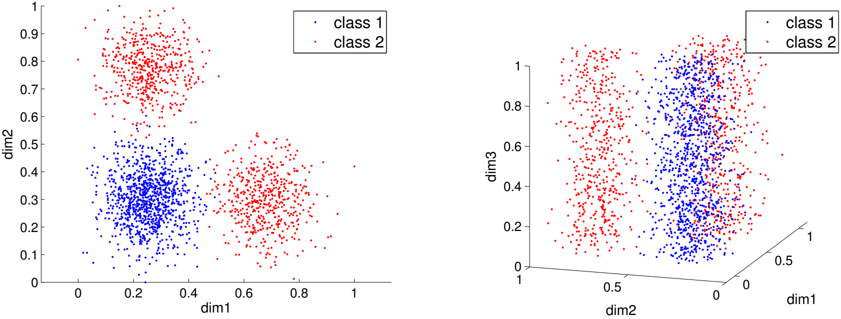
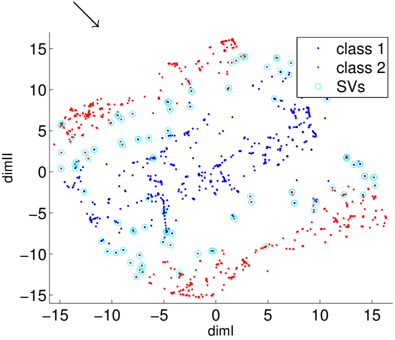
   much less effort than sampling in the high-dimensional space
3. Project the samples up to the original space
4. Classify them

An illustration: ”high”-dimensional data



An illustration: dimensionality reduction

Train the classifier and project data to 2D



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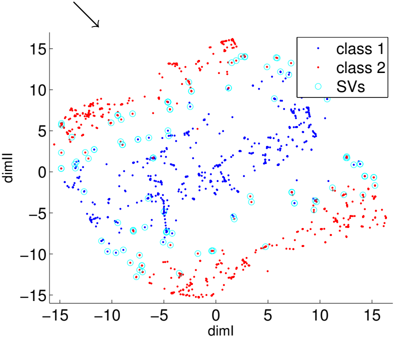
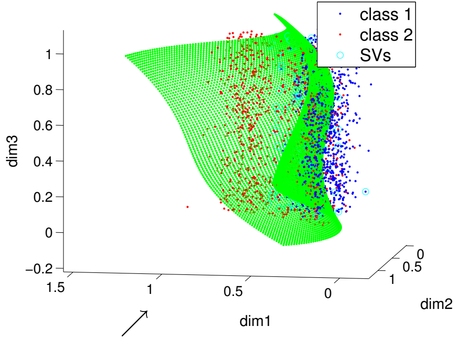
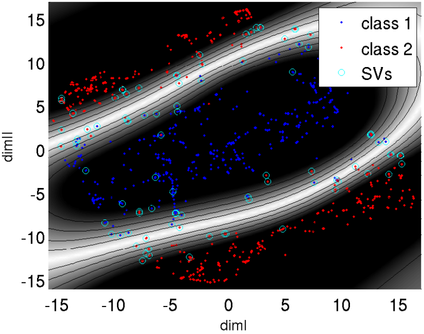




Sample in 2D and project up

An illustration: border visualization

- contours code the distance from the class boundaries



Inverting the dimensionality reduction

Assume n training data $\boldsymbol{x}_i \in \mathbb{R}^D$ accompanied by labels $l_i \in L$

- Use a nonlinear dimension reduction method to produce a low-dimensional embedding $p(\boldsymbol{x}_i) = \boldsymbol{y}_i \in \mathbb{R}^2$

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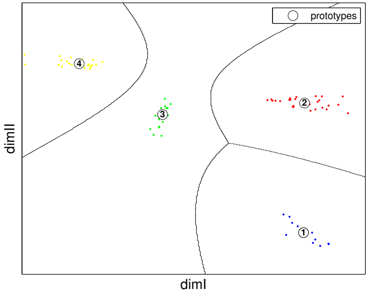
  with parameters α, the kernel and possible kernel parameters
- Find the least squares solution for α of the reconstruction error

$$E = \sum_j \left\| \boldsymbol{x}_j - p^{-1}(\boldsymbol{y}_j) \right\|^2$$

Application

- Gene Expression Data Set (Ground truth available)
- Visualization via LLiRaM LVQ [Bunte, Dissertation]



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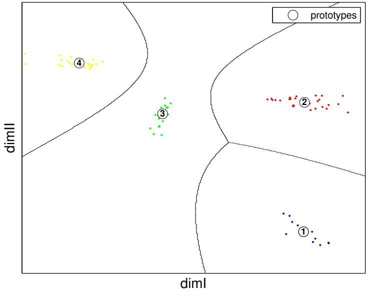

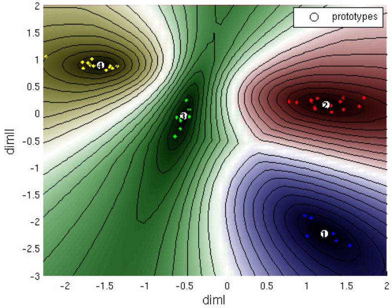

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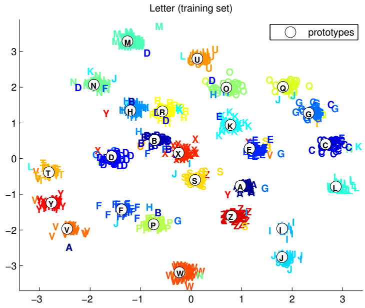
- Letter Recognition Data Set
- Visualization via LiRaM LVQ + t-sne [Bunte et.al 2012]



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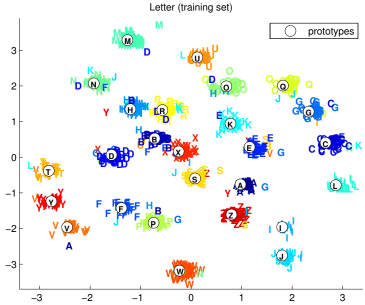

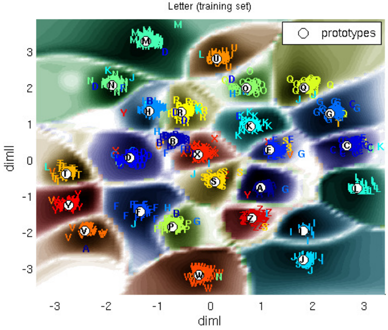

Conclusions & Future work

Conclusion:

- The visualization of classification boundaries is possible
- First experiments showed promising results

Future Work:

- What if certain dimensions are more relevant for classification? (Fisher information, classifier)
- Learning of hyper-parameters

Thank You For Your Attention!