

2009 Quality and Productivity Research Conference

Neural network time series classification of changes in nuclear power plant processes

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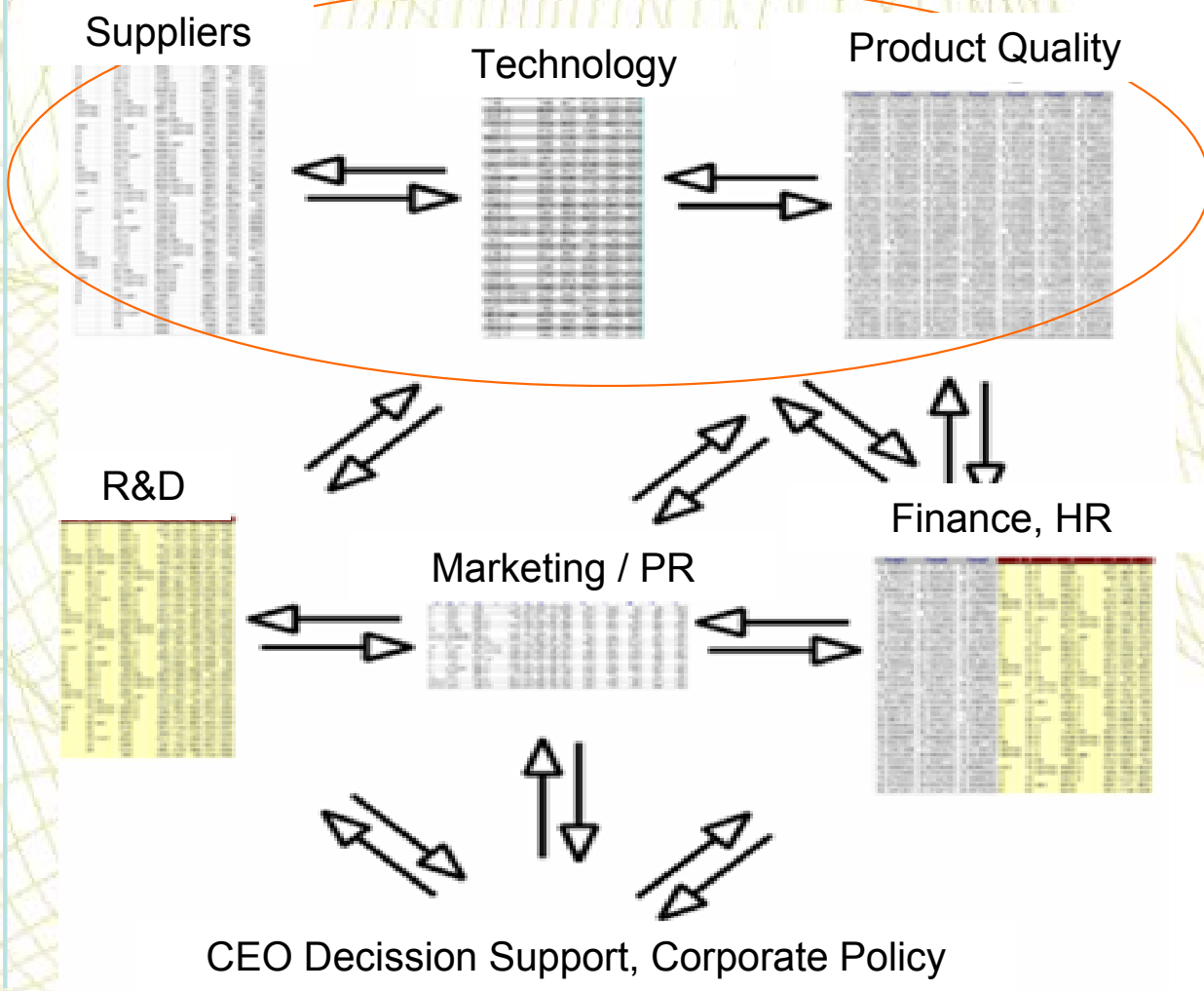
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Statistical models deployment in industry, technology and research



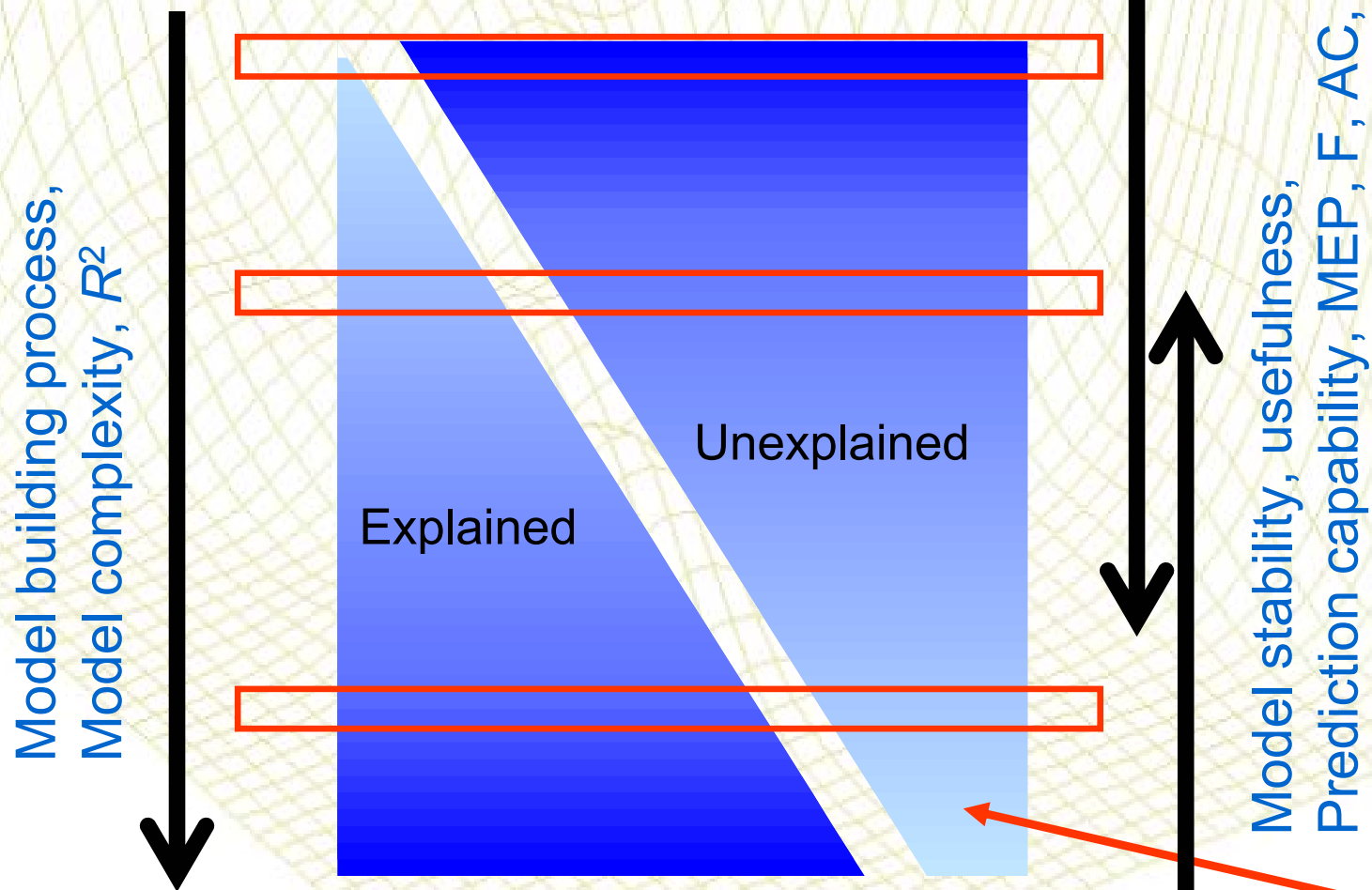
Data and Information Flow in a Company

| Customer | Environmental | Safety |
|----------|---------------|--------|
| 0.135 | 0.125 | 0.080 |
| 0.078 | 0.160 | 0.090 |
| 0.032 | 0.300 | 0.062 |
| 0.422 | 0.430 | 0.140 |
| 0.407 | 0.000 | 0.120 |
| 0.865 | 0.430 | 0.242 |
| 0.991 | 0.007 | 0.146 |
| 0.907 | 0.004 | 0.090 |
| 0.995 | 0.972 | 0.004 |
| 0.984 | 0.244 | 0.176 |
| 0.984 | 0.664 | 0.159 |
| 0.775 | 0.986 | 0.019 |
| 0.138 | 0.162 | 0.218 |
| 0.663 | 0.306 | 0.409 |
| 0.209 | 0.376 | 0.032 |
| 0.150 | 0.094 | 0.003 |
| 0.207 | 0.460 | 0.007 |
| 0.489 | 0.449 | 0.772 |
| 0.700 | 0.720 | 0.100 |
| 0.905 | 0.735 | 0.454 |



Model building process

$$X = \text{MODEL} + \text{NOISE}$$



$$Q \propto \frac{1}{\sigma^2}$$

- Gradual variability explanation/reduction
- Criterion: practically applicabe (empirical) prediction model

Unexplained (-able), inherent variability

Prediction model application examples

Steel works – Predict/classify mechanical&physical properties based on chemistry&technology parameters

Brewery – Find relationship between (bio-)chemistry and sensoric evaluation/classification of beer

Pharmaceutical/Cosmetics – Find quantitative structure – activity relationship (QSAR)

Financial – Classify loans, credit scoring, risk analysis

Climatology/Environment – Antarctica-based solar activity and ozone prediction, Industrial air pollution analysis

Regression, PCA, PLS, CART, ANN, ANNTS, SVM

Nuclear power plant time series



The Plant

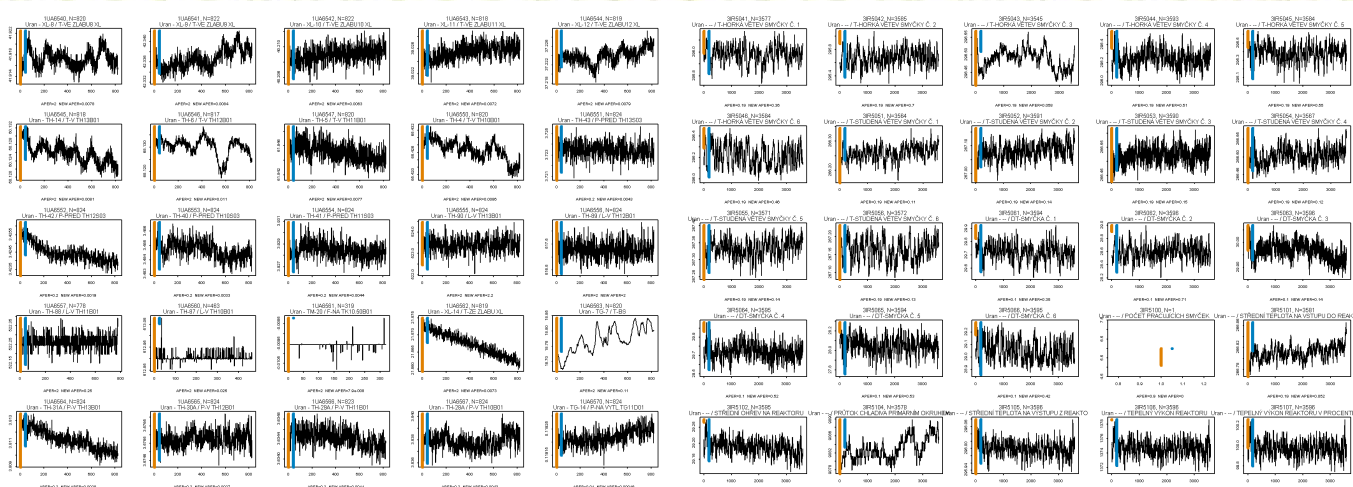


The Reactor



The Sensors

Temperatures, energy flow rates, meta-stable process modes



Driven by complicated nonlinear local physical processes

Some modes more important than others

Classify known metastable states Y of the process using process time series

The idea -

Sample space (n) \rightarrow Variable space (m) \rightarrow Model parameter space (p)
 $n > m \geq p$

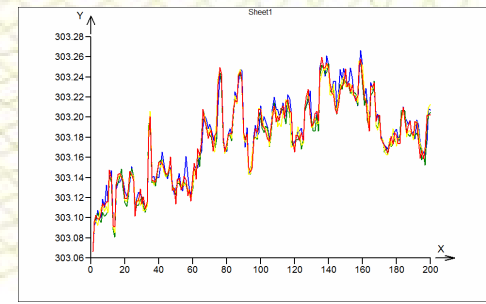
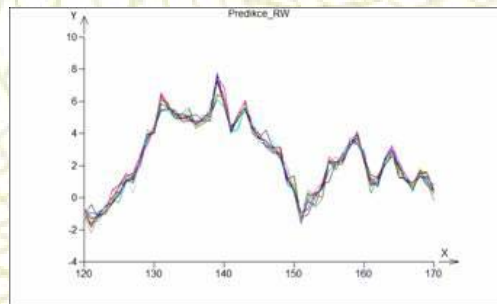
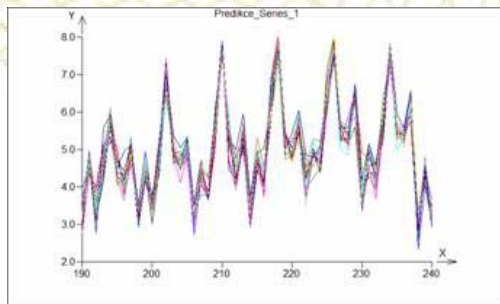
Use parameters as predictors in suitable classification model

$$Y = \Theta(p, \alpha)$$

Time series model – (Differential) ANN Autoregresion

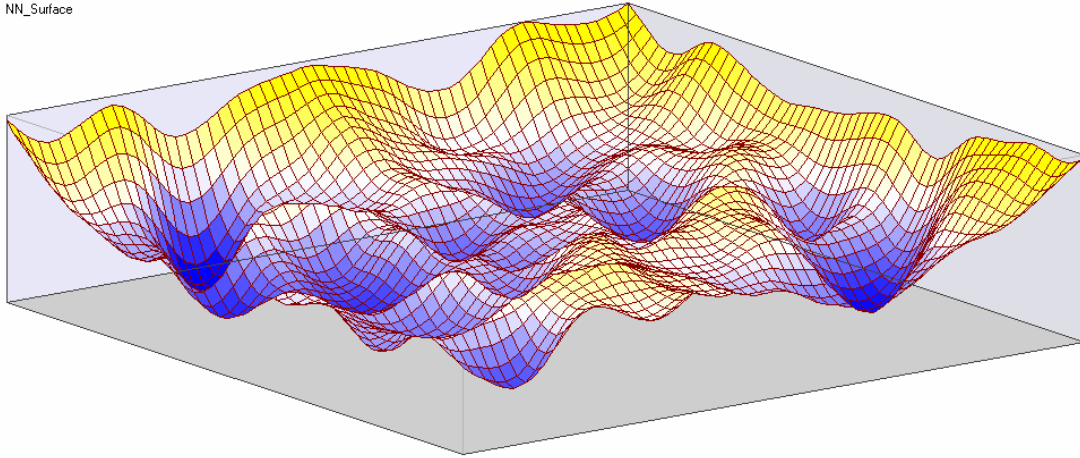
$\mathbf{x}_t = Z_{NNAR}(\mathbf{x}_{t-k})$ $\mathbf{x}_t = Z_{NNAR}(\mathbf{x}_{t-k}, \Delta\mathbf{x}_{t-k})$ $m \geq p$ is usually not met

Time series examples -



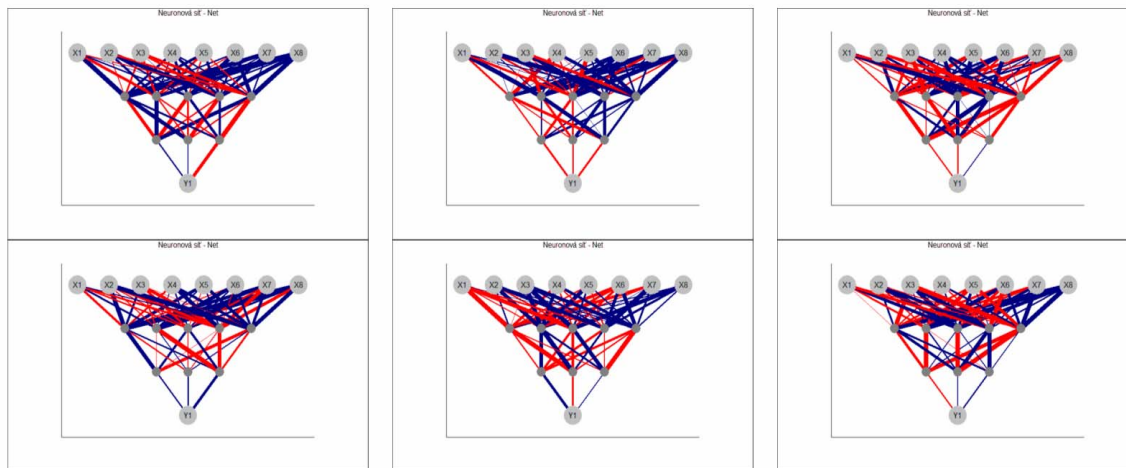
ANN solution stability problem

NN_Surface



$$R(\theta) = \sum_j \left(y_j - f(\theta, \mathbf{x}_j) \right)^2$$

Adaptive Gauss-Newton optimization strategy

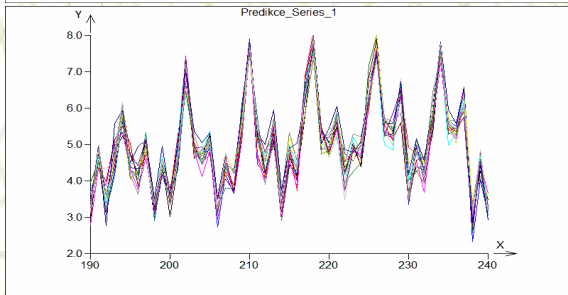
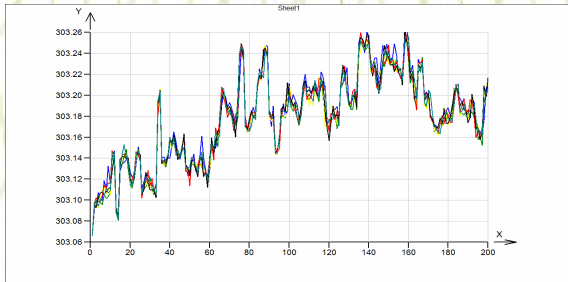


Non-convex error surface
Multiple local minima

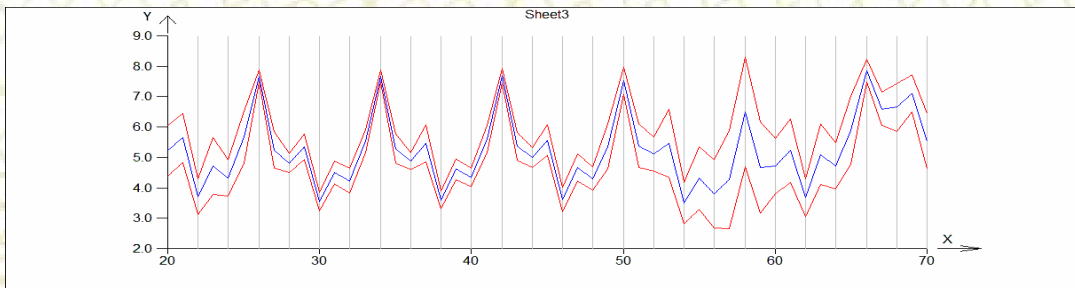
Many different „good“ solutions to the same problem

Error Distribution Estimation

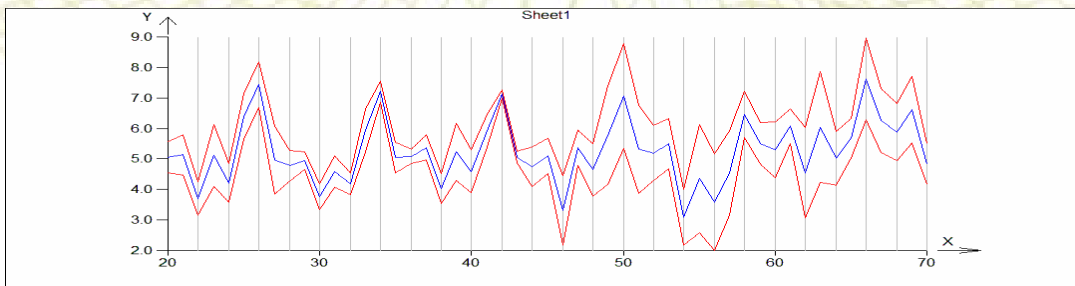
Take advantage of the ANN models drawback
use instability as „bootstrap“



Re-construct confidence intervals of prediction

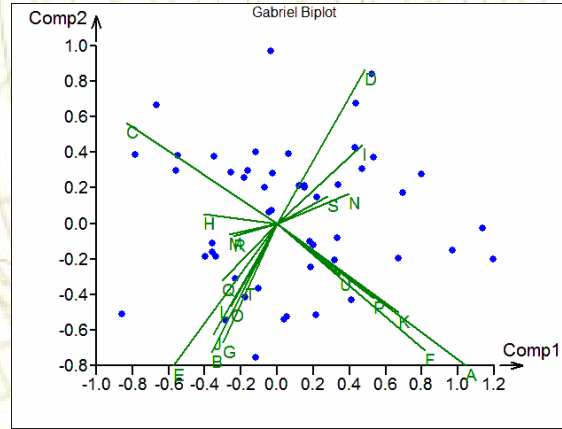
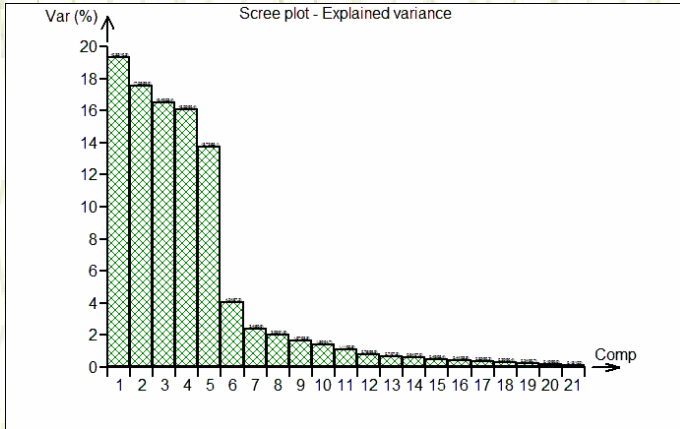


Robustification by choosing
non-Eucleidian distance for
optimizing the fit



$$R(\theta) = \sum_j \left(y_j - f(\theta, \mathbf{x}_j) \right)^r; 1 < r < 2$$

Reducing parameter space dimension



PCA reveals inherent dimensionality of ANN weights $D(p) < p$

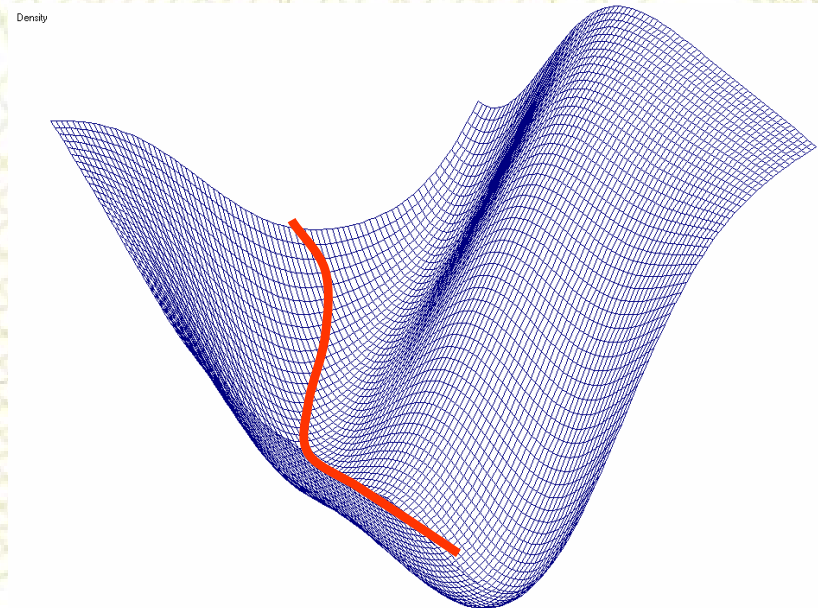
Significant principal components of model parameters appear to be a good predictor

$$\begin{pmatrix} \frac{\partial w_1}{\partial w_1} & \dots & \frac{\partial w_1}{\partial w_p} \\ \vdots & \frac{\partial w_i}{\partial w_j} & \vdots \\ \frac{\partial w_p}{\partial w_1} & \dots & \frac{\partial w_p}{\partial w_p} \end{pmatrix}$$

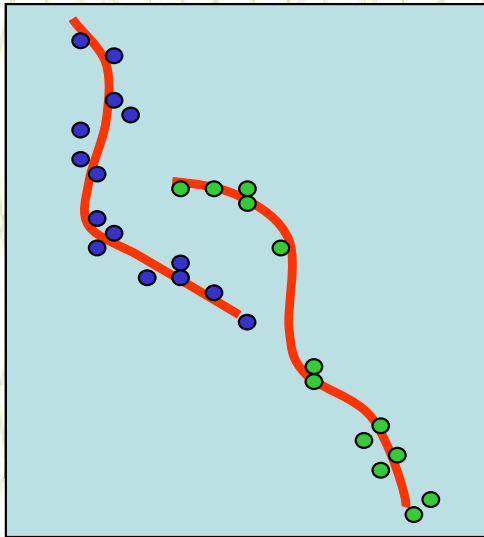
A nonlinear system defining a subspace in the parameter space with lower inherent dimensionality $p' < p$ thus allowing stable prediction in p' .

subject to

$$\frac{\partial R(w)}{\partial w_i} \leq \delta; \delta \geq 0$$



Model classification



Linearly non-separable data on first p' components
 Suitable for SVM separation

$$\min_{\mathbf{w}, b, \xi, \rho} \quad \frac{1}{2} \mathbf{w}^T \mathbf{w} - \nu \rho + \frac{1}{l} \sum_{i=1}^l \xi_i$$

subject to

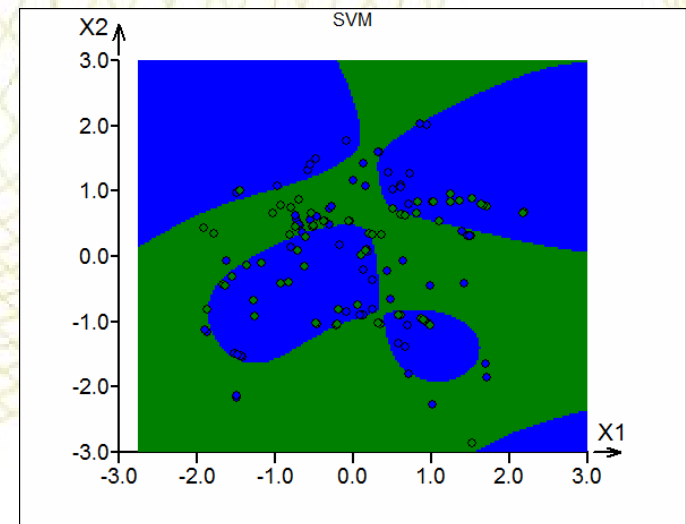
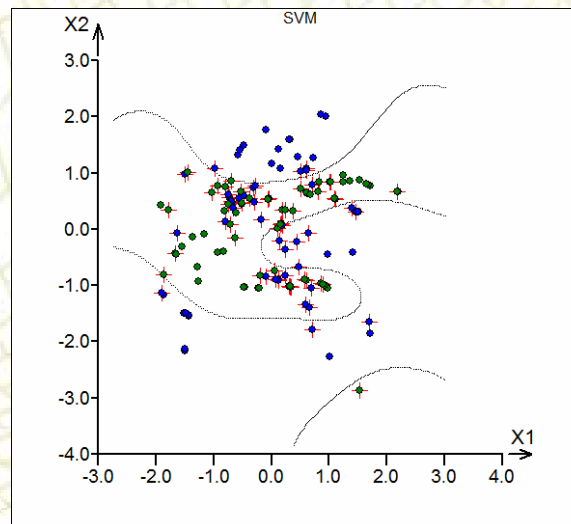
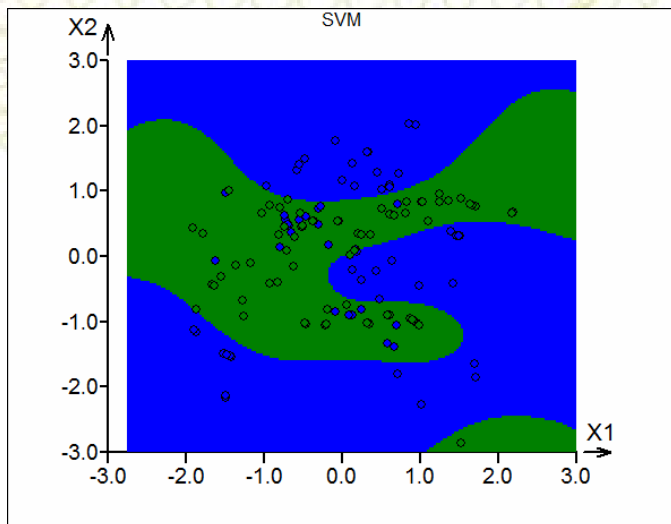
$$y_i (\mathbf{w}^T \phi(\mathbf{x}_i) + b) \geq \rho - \xi_i,$$

$$\xi_i \geq 0, i = 1, \dots, l, \rho \geq 0.$$

| | |
|-------------|-----------|
| svm_type | c_svc |
| kernel_type | RBF |
| Gamma | 0.5 |
| cases | 153 |
| variables | 5 |
| nr_class | 2 |
| total_sv | 49 |
| label | 1 2 |
| nr_sv | 26 23 |

| | |
|----------------|-------|
| Misclass Table | |
| Correct | 151 |
| Misclass | 2 |
| Misclass Rate | 0.013 |

RBF Kernel SVM projection to pc₁, pc₂, m.r.=0.17



Conclusion

Applicability to static and dynamic multivariate problems

Significant dimension reduction

Applications in brewery, pharma, steel, medicine

(-) Computationally extensive

(-) No simple model

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