

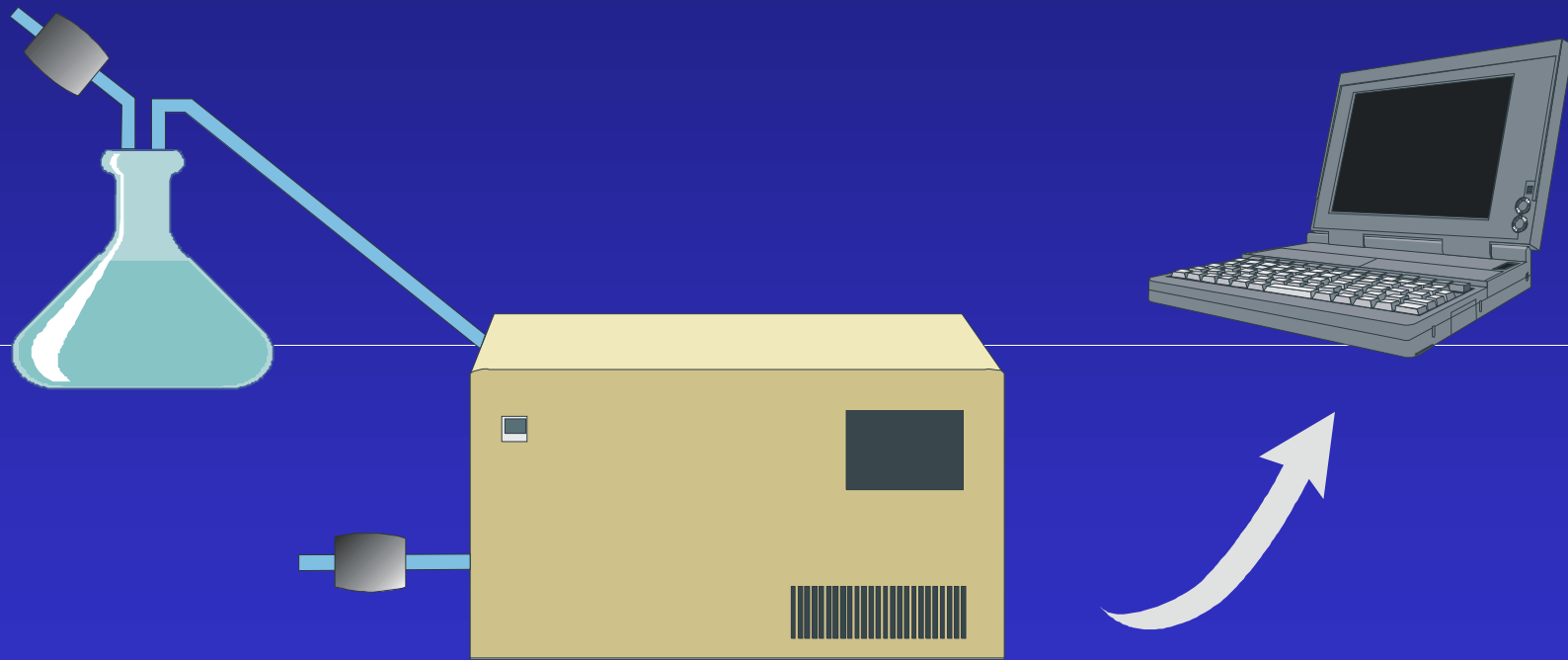


# Food Quality Assurance Applying a Sophisticated Neural Network to Olfactory Signals

Roland Linder, Siegfried J. Pöppel

- Methods
- Data
- Results
- ACMD – what does it mean?
- Conclusions

# Portable Electronic Nose (PEN)



Sample

Signal Detection Unit

Signal Processing Unit  
(Classification)

# We are not the first ones who use an EN

- Marsili, RT: Shelf-life prediction of processed **milk** by solid-phase microextraction, mass spectrometry, and multivariate analysis. J Agric Food Chem 2000;48(8):3470-5.
- Blixt Y, Borch E: Using an electronic nose for determining the spoilage of vacuum-packaged **beef**. Int J Food Microbiol 1999;46(2):123-34.
- Young H, Rossiter K, Wang M, Miller M: Characterization of Royal Gala **apple** aroma using electronic nose technology-potential maturity indicator. J Agric Food Chem 1999;47(12):5173-7.

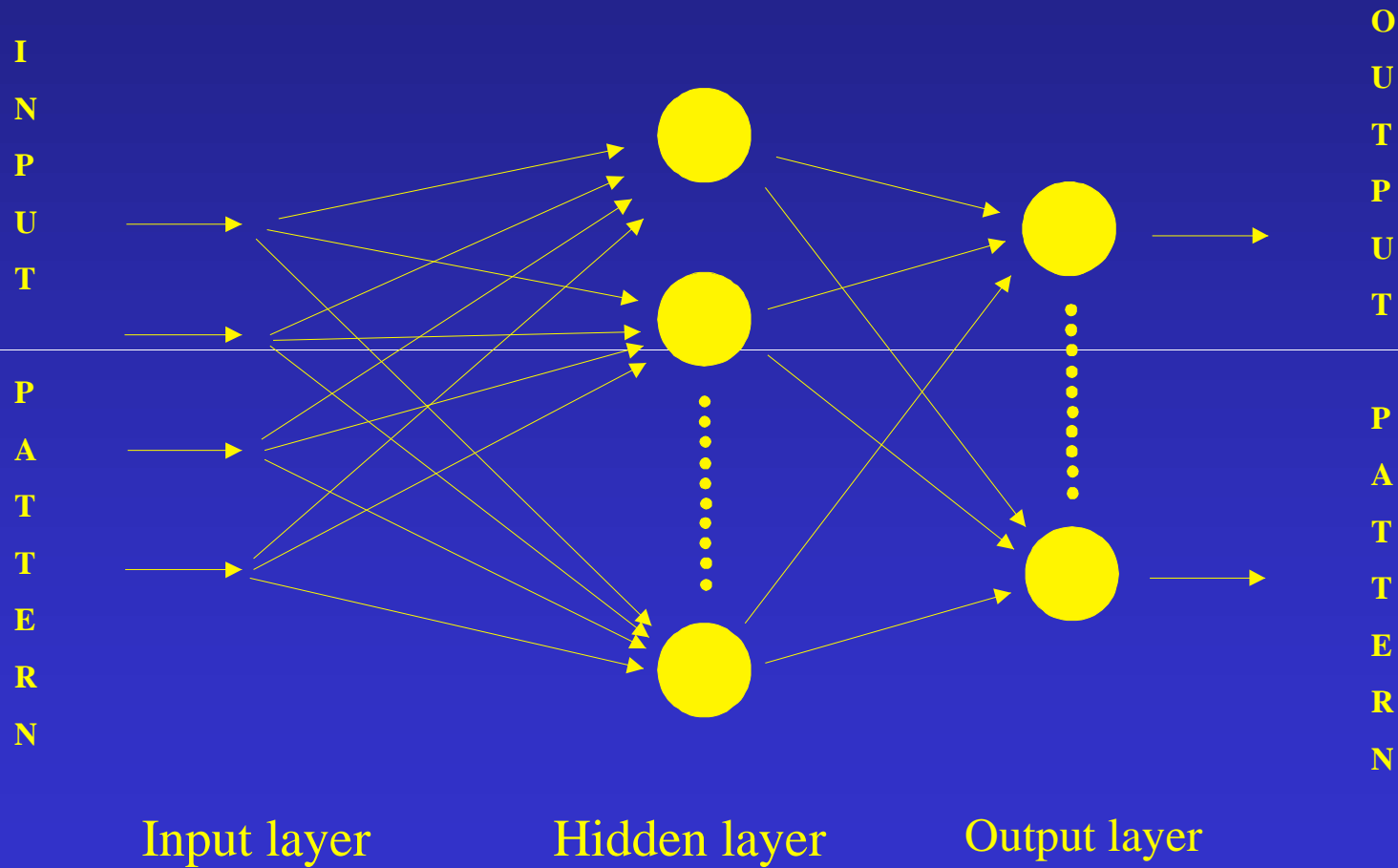
# We are not the first ones who use an Artificial Neural Network (ANN)

- Boilet P, Hines EL, John S, Mitchell J, Lopez F, Gardner JW, Llobet E, Hero M, Fink C, Gongora M: Detection of eye **bacteria** causing eye infections using a **neural network** based electronic system. In Gardner JW, Persaud KC (eds.): **Electronic Noses** and Olfaction, IOP Publishing Ltd, Bristol, 2000, 189-196.
- Llobet E, Hines EL, Gardner JW, Franco S: Non-destructive **banana** ripeness determination using a **neural network**-based **electronic nose**. Meas Sci Technol 1999;10(6):538-548.
- Hines EL, Llobet E, Gardner JW: **Neural network** based **electronic nose** for **apple** ripeness determination. IEE Electronic Letters 1999;35(10):821-823.

## What is the benefit of using an ANN ?

- Non-linearities
- Dependencies between variables
- No assumptions of any well-defined distributions

# How does an ANN work?



# Learning algorithms we used

- Standard Backpropagation (**BPN**)

[Rumelhart, Hinton & Williams 1986]

- Resilient Propagation (**RPROP**)

[Riedmiller & Braun 1993]

- Adaptive Propagation (**APROP**)

[Linder, Wirtz & Pöppel 2000]

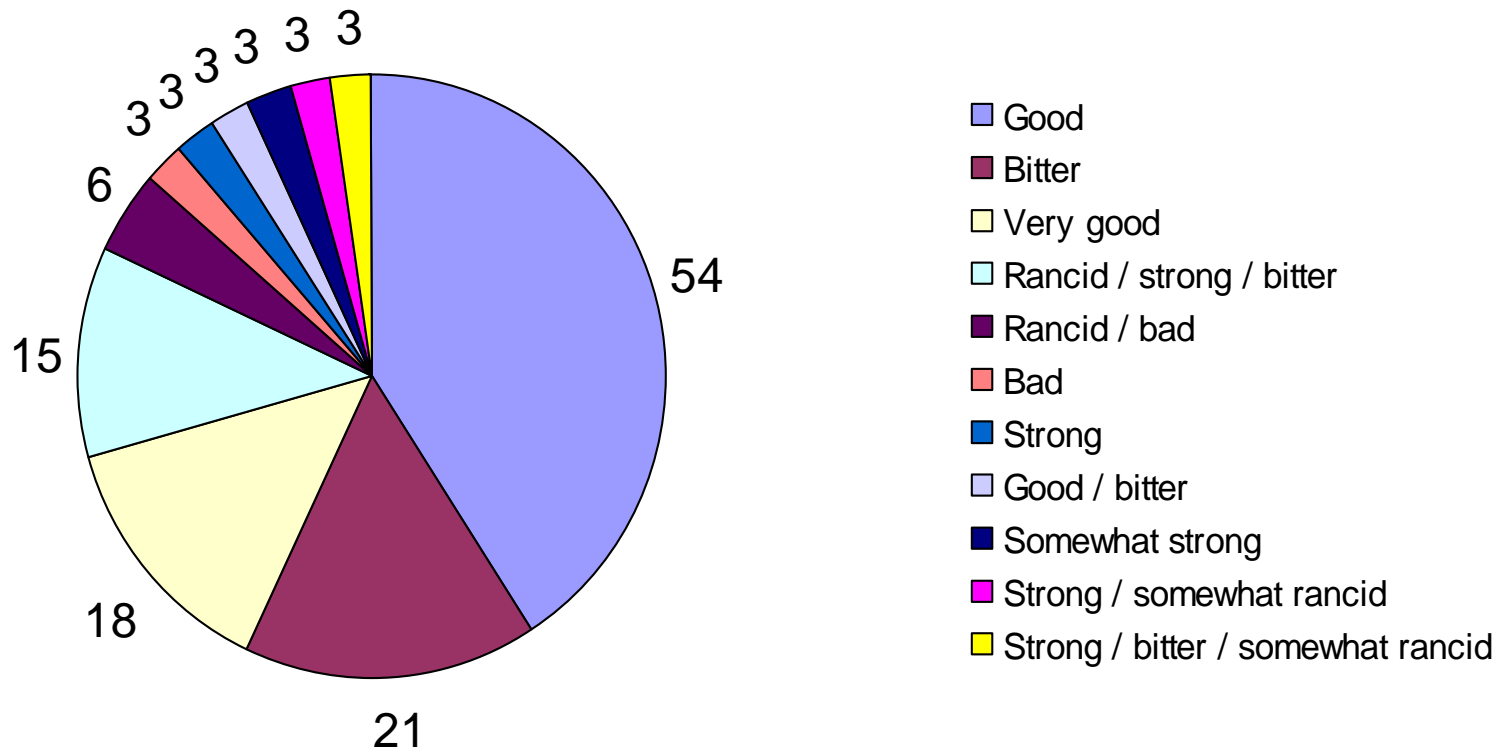
# Standard Backpropagation (BPN)

$$\Delta \mathbf{w}_{jk}^{new} = \eta \cdot \frac{\partial \mathbf{E}}{\partial \mathbf{w}_{jk}} + \alpha \cdot \Delta \mathbf{w}_{jk}^{old}$$

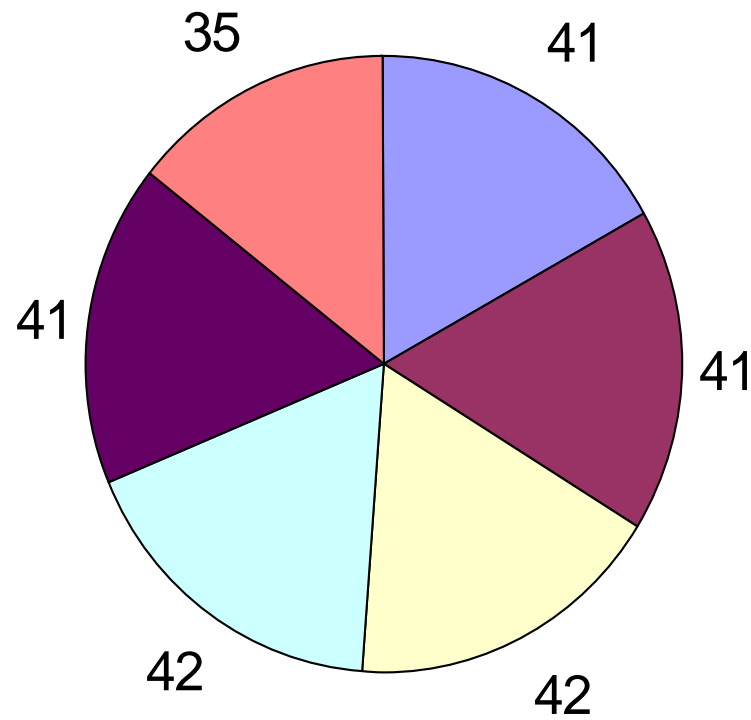
# Resilient Propagation (RPROP)

$$\Delta w_{ij} = \begin{cases} -\Delta_{ij} & , \text{ if } \frac{\partial E}{\partial w_{ij}} > 0 \\ +\Delta_{ij} & , \text{ if } \frac{\partial E}{\partial w_{ij}} < 0 \\ 0 & , \text{ otherwise} \end{cases}$$

# Classifying Edible Oil

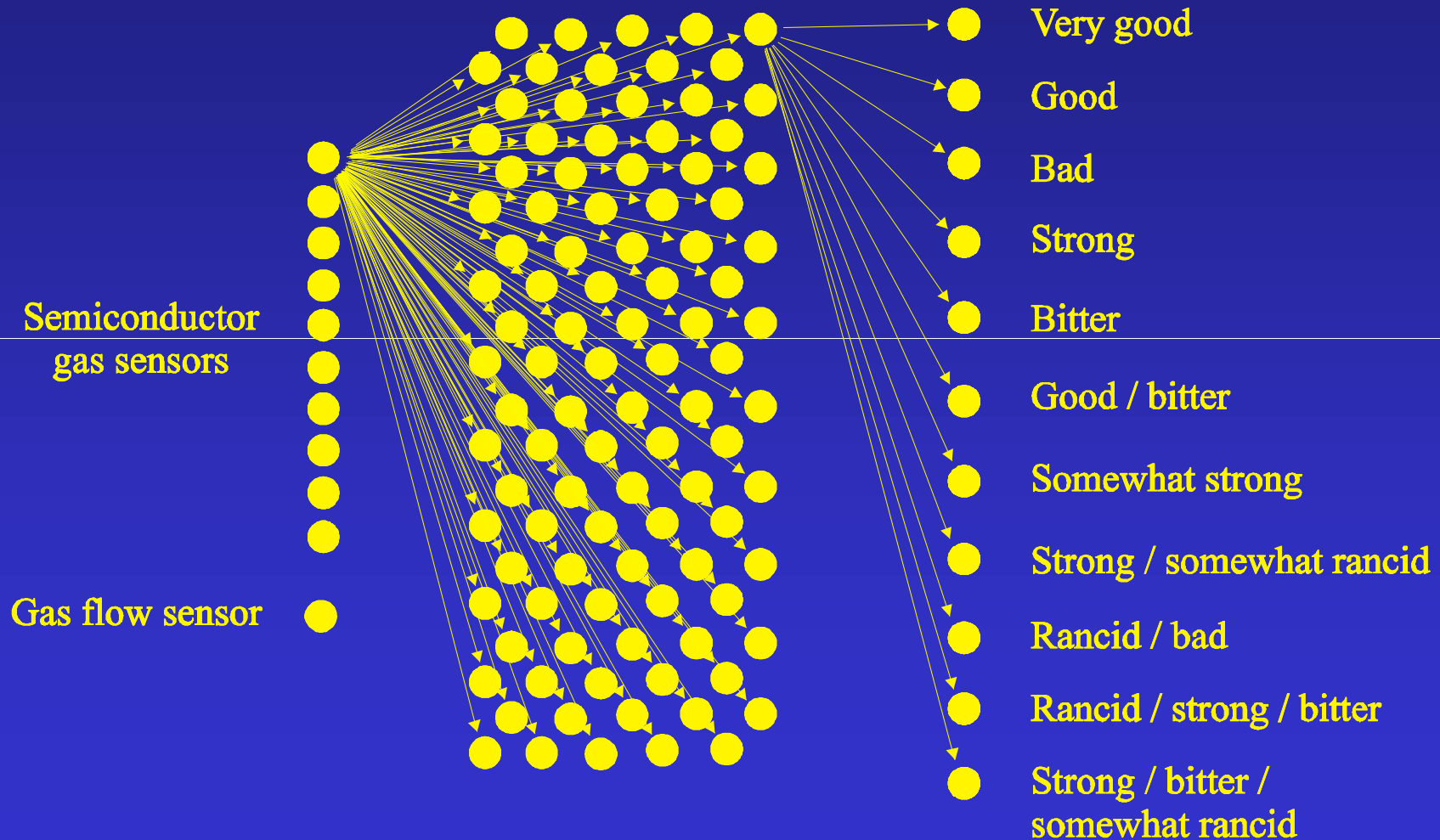


# Classifying Honey

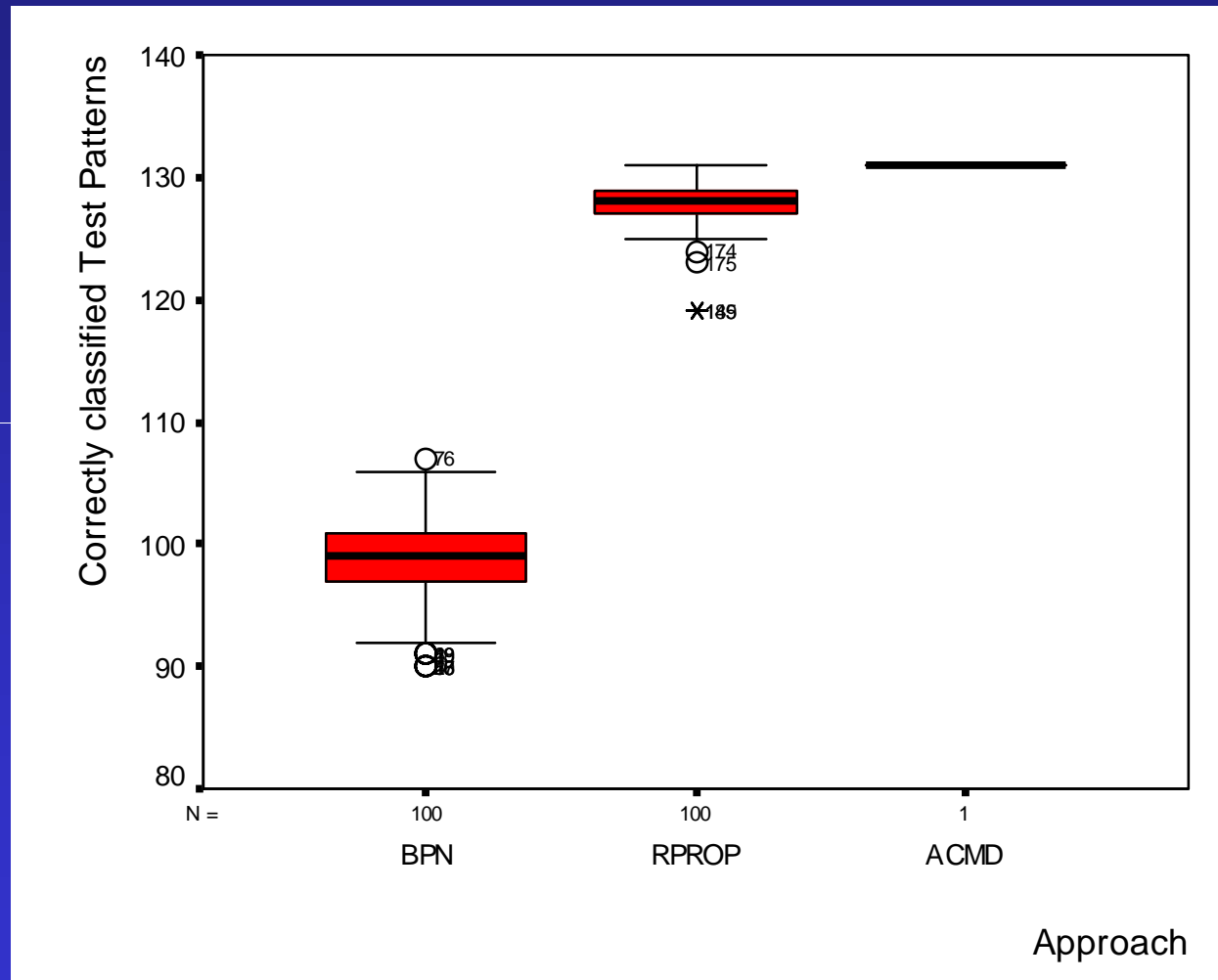


- Type 1
- Type 2
- Type 3
- Type 4
- Type 5
- Type 6

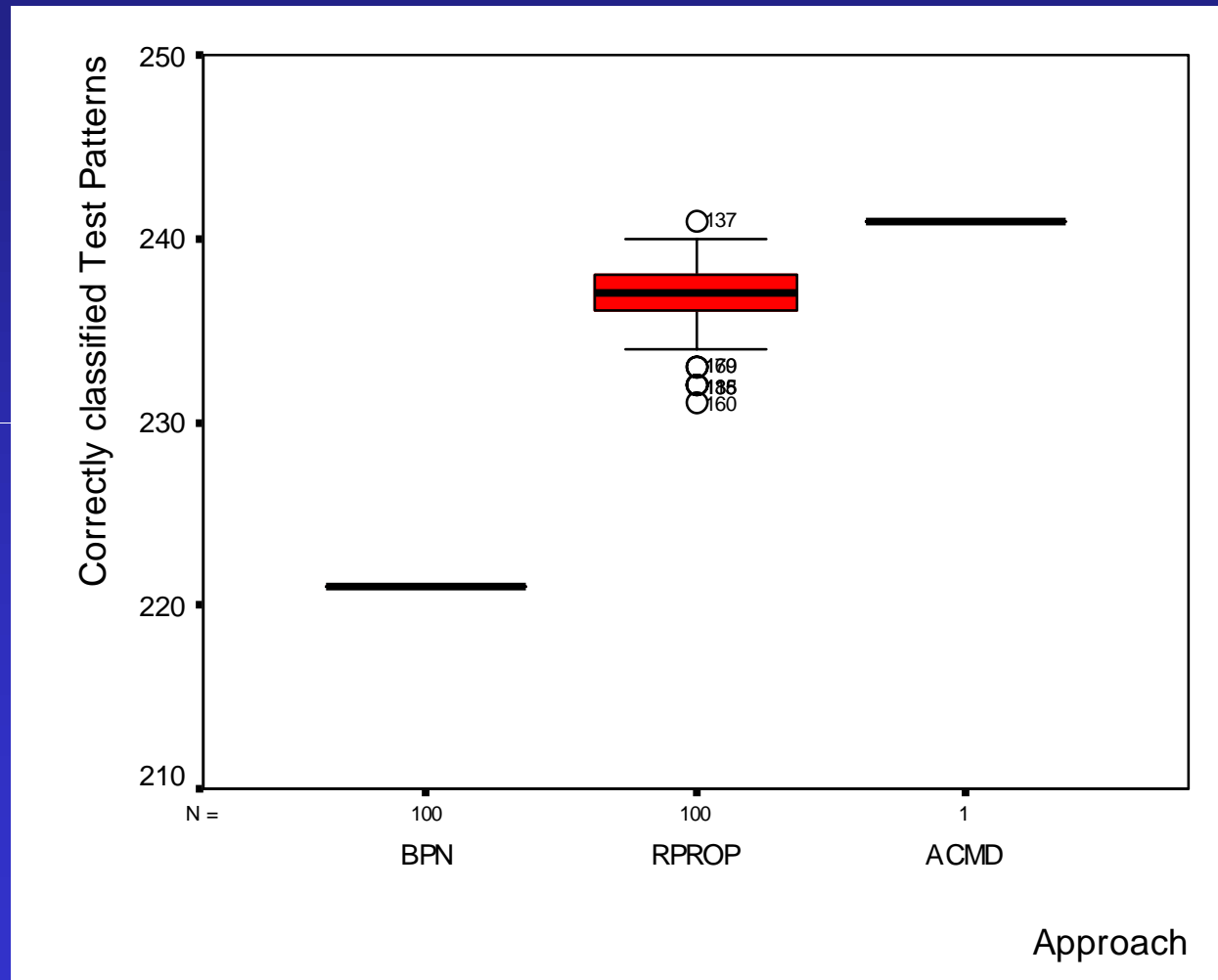
# The Neural Network



# Results: Edible Oil



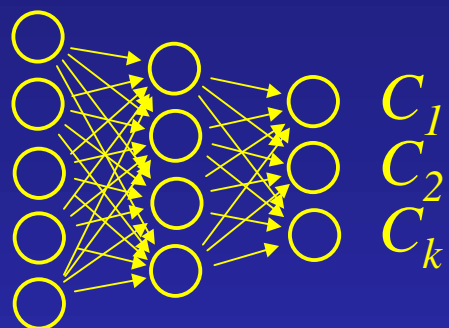
# Results: Honey



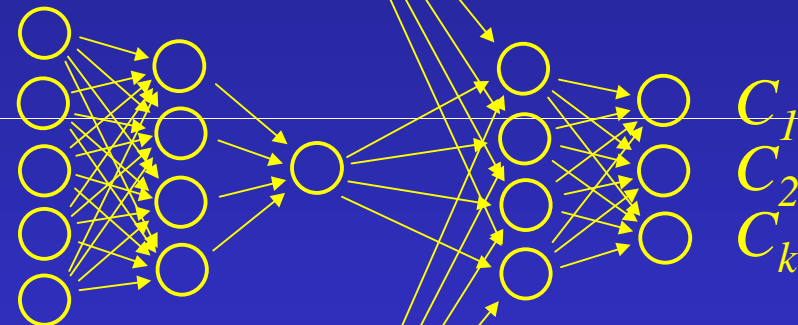
# Strategies – an Overview

Strategy	Generalisation	Speed	No tuning
Multi-neural-network	x	(x)	
Refining the Target output	x		
Early stopping	x		x
Avoiding weight sets from oscillating phases	x		
Oversizing the network	x		x
Network ensemble	x		
Exclusion Strategy	x		
Adaptive propagation		x	
Modifying the error function	x		
Modifying the derivation	x		
Varying the learning rate	x		x
Stop oscillating and unsuccessful learning		x	
Optimising the software		x	
Approximation of the exponential function		x	

# Multi-Neural-Network



$k$ -class problem



$k$  two-class problems

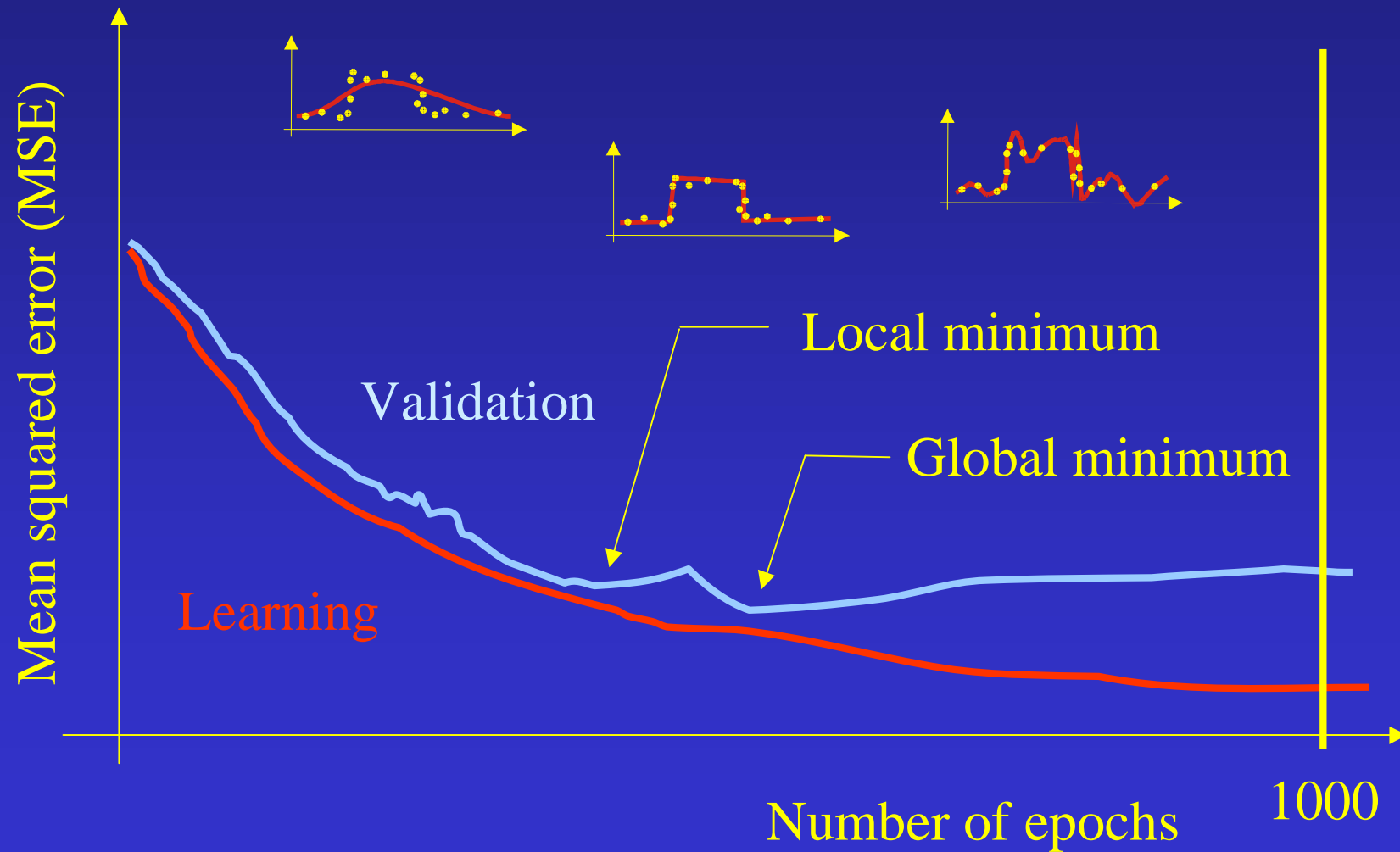
# Multi-Neural-Network

- Simple functions can be better learned than complex functions.
- Learning may be faster and parallel computing is possible.
- Weight analysis is easier for modular networks.
- Better generalisation performance due to the cascaded architecture.

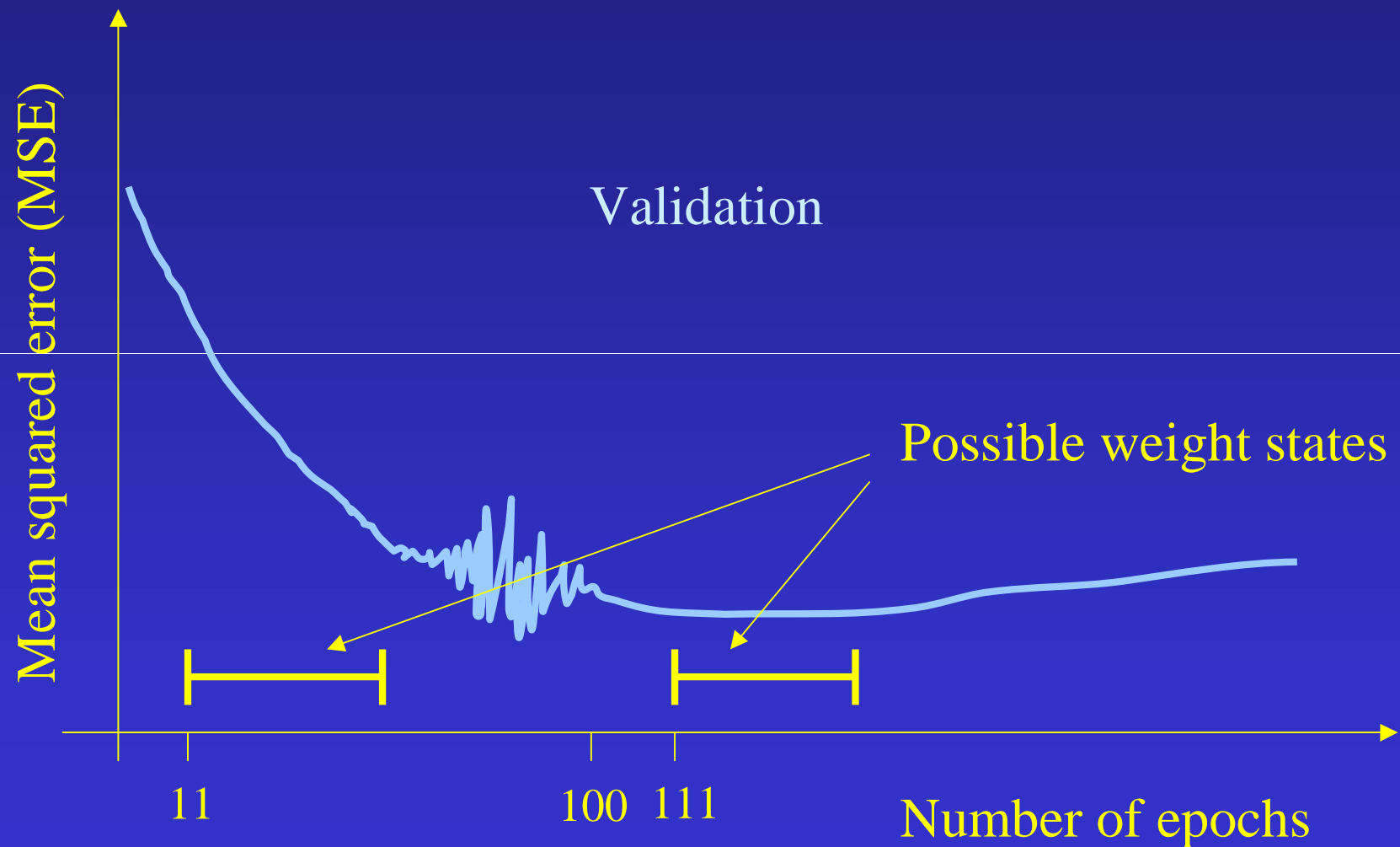
# Refining the Target Output

Target output (1-out-of-C code)	Real output after 1000 epochs	Refined target output	Target – real output
1	0.7	1	0.3
0	0.3	0.3	0
0	0.1	0.1	0
0	0.2	0.2	0
0	0.6	0	0.6
0	0.1	0.1	0
0	0.1	0.1	0

# Early Stopping



# Avoiding Weight Sets from Oscillating Phases



# Oversizing the Network

**Lawrence, Giles, Tsoi:** „We further support the observation that larger networks can produce better training and generalization error.“

**Caruana:** „Large networks rarely do worse than small networks.“

**Hassoun, Cherkassky, Hanson, Oja, Sarle, Sudjianto:** „It is clear that too many parameters in some nonparametric models can be grievous, however with many Neural Networks, more parameters can actually improve things.“

**Kröse, van der Smagt:** „The addition of extra parameters can decrease the chance of becoming stuck in local minima or on ‚plateaus‘, etc.“

**Bartlett:** „Neural networks often perform successfully with training sets that are considerably smaller than the number of network parameters.“

**Weigend:** „Large networks generalize better than small ones.“

**Rumelhart:** „Adding a few more connections creates extra dimensions in weight-space and these dimensions provide paths around the barriers that create poor local minima in the lower dimensional subspaces.“

# Network Ensemble

Network 1

A

B

C

D

E

Network 2

A

B

C

D

E

Network 3

A

B

C

D

E

Network 4

A

B

C

D

E

Network 5

A

B

C

D

E

■ Learning set    ■ Validation set

# Exclusion Strategy

1 test pattern (with unknown class assignment)



Ensemble, trained with  $n$  classes

1) 0.9 2) 0.2 3) 0.8 4) ...



Ensemble, trained  
with class 1 + 2

Ensemble, trained  
with class 1 + 3

...

Ensemble, trained  
with class 1 +  $n$

...

1) 0.86 3) 0.88



Result: Class 3

# Adaptive Propagation (APROP)

$$S_{l,n} = \frac{1}{\sqrt{\sum_{i=1}^p \delta_{l,n,i}^2}}$$

# Modifying the Error Function

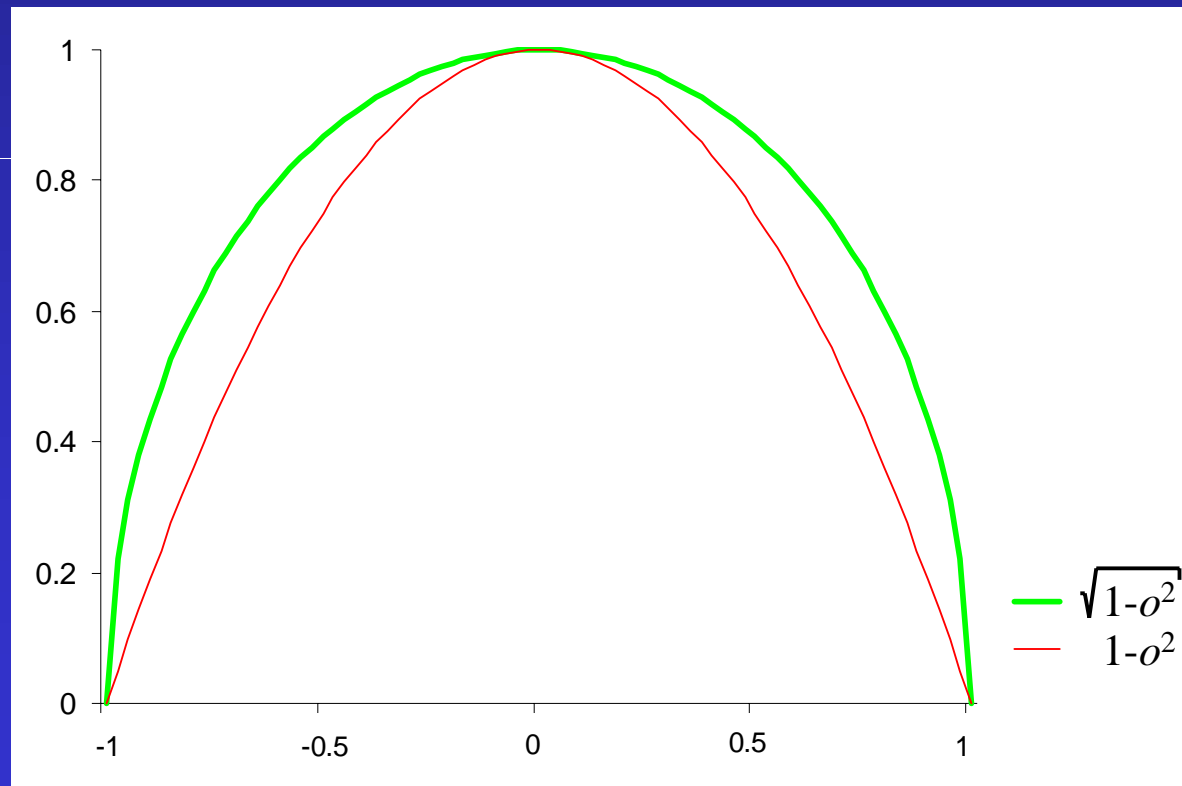
$$\delta_{\text{output layer}} = (1 - o^2) \cdot \text{sign}(t - o) \cdot (t - o)^2$$

Example:

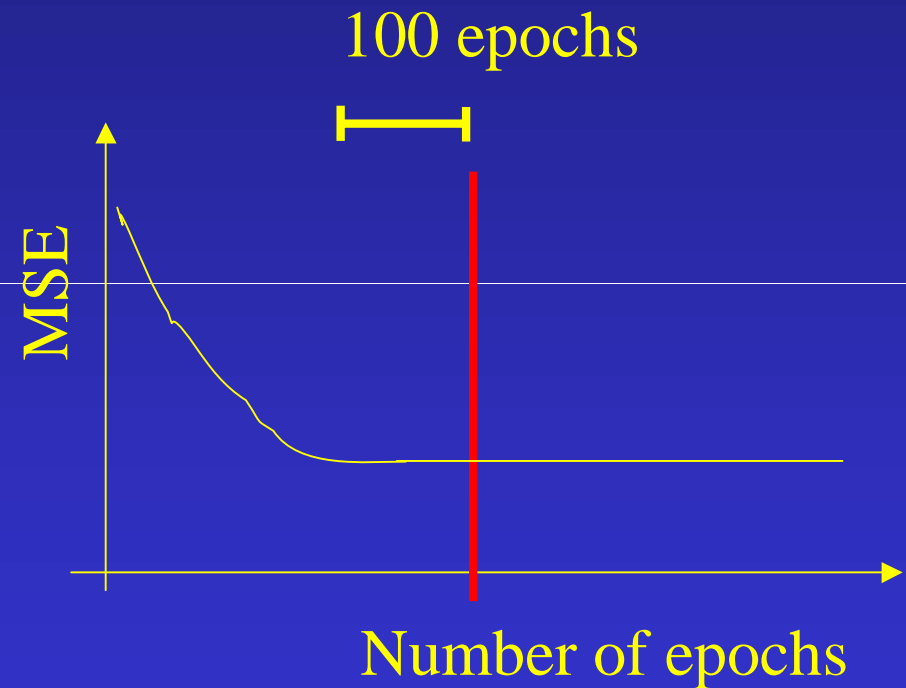
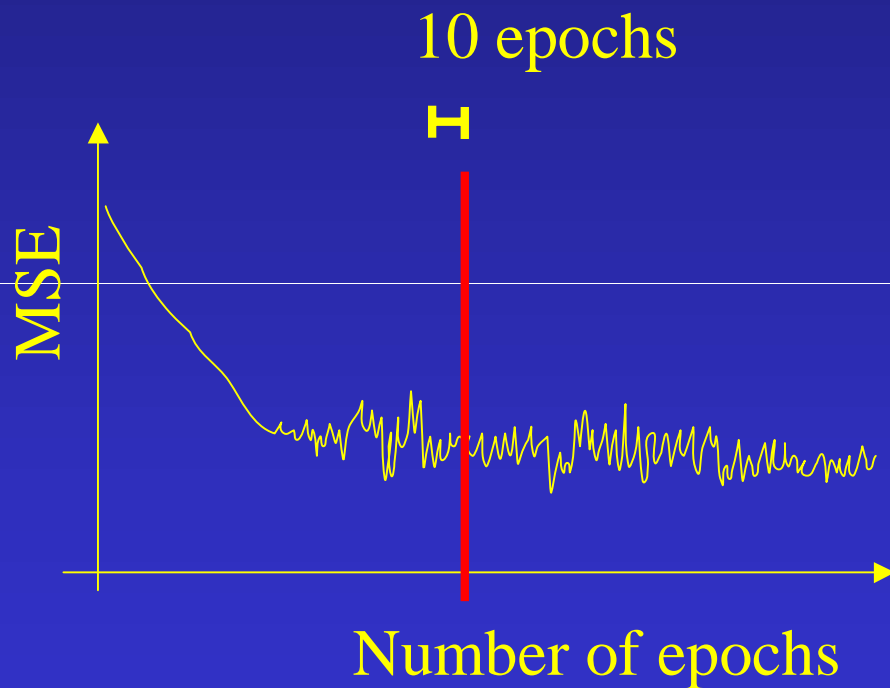
	Pattern 1	Pattern 2	Quotient
$ t - o $	0.8	0.2	4
$(t - o)^2$	0.64	0.04	16

# Modifying the Derivation

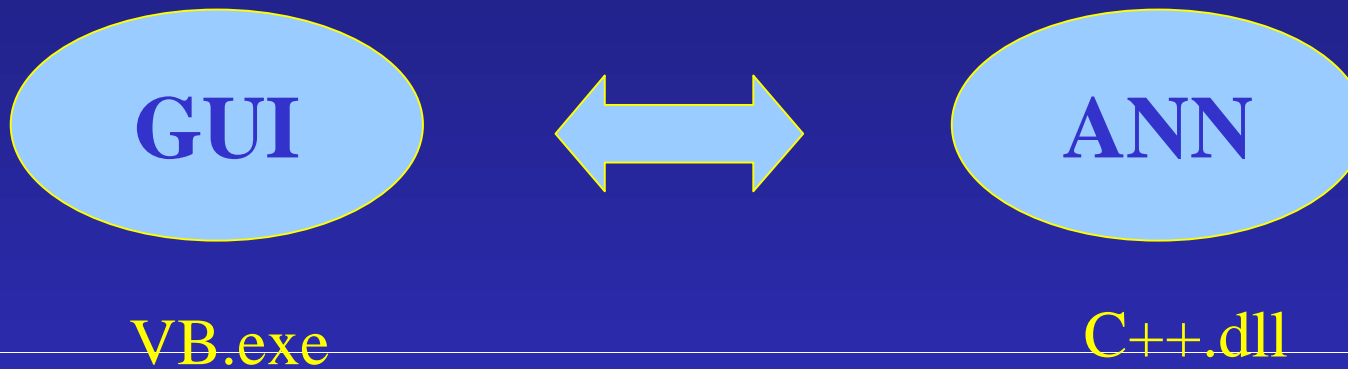
$$\delta_{\text{output layer}} = \sqrt{1 - o^2} \cdot \text{sign}(t - o) \cdot (t - o)^2$$



# Stop Oscillating and Unsuccessful Learning



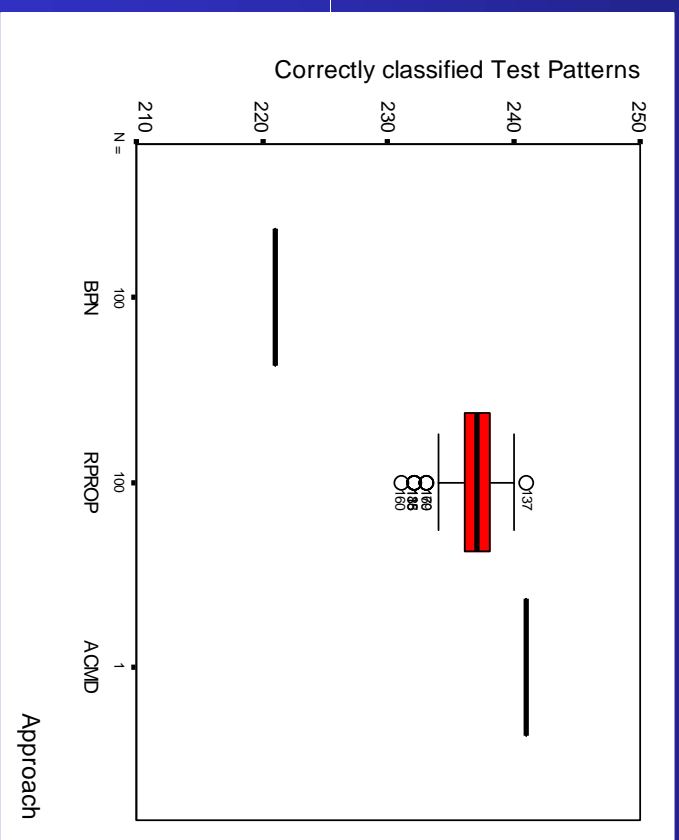
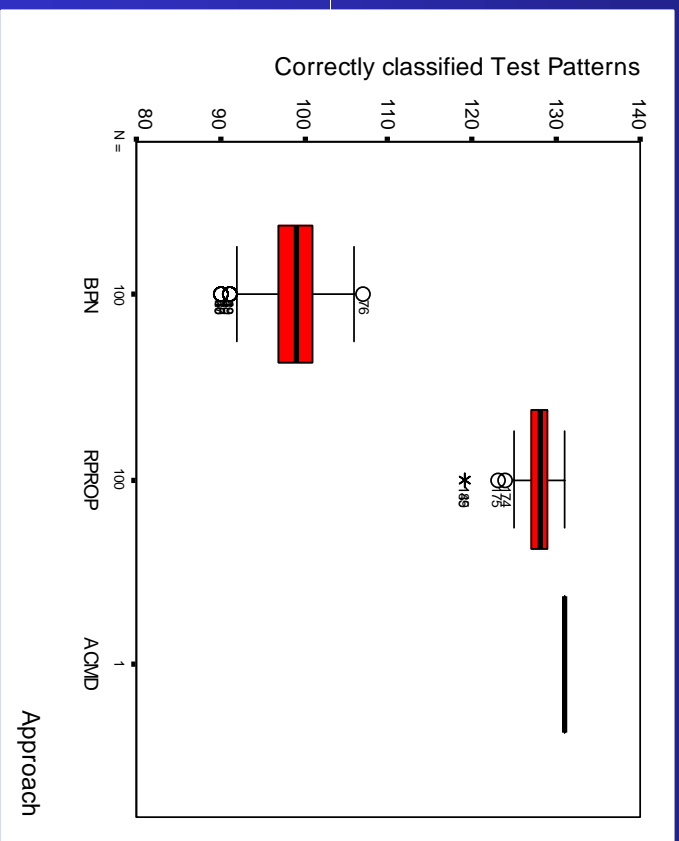
# The Software



- Compiler settings optimised for speed
- Multithreaded Code
- Extensive use of pointers
- Dynamic arrays
- Avoidance of if-statements or consecutive instructions that hamper pipelining



# Results



Edible Oil

Honey

# Conclusion

If you decide to use an ANN for pattern recognition of EN signals or whatever biosignals – it is worthwhile to **consider suitable ANN strategies.**

Thank you!

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