Computational Intelligence

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Plan for Today

- Application Fields of ANNs
  - Classification
  - Prediction
  - Function Approximation
- Radial Basis Function Nets (RBF Nets)
  - Model
  - Training
- Recurrent MLP
  - Elman Nets
  - Jordan Nets

Classification

given: set of training patterns (input / output)

$\tilde{x}_i$ (input), $\tilde{y}_i$ (output)

output = label
(e.g. class A, class B, ...)

parameters

$$f(x; (\tilde{x}_1, \tilde{y}_1), \ldots, (\tilde{x}_m, \tilde{y}_m), w_1, \ldots, w_n) \rightarrow \hat{y}$$

- x: input (unknown)
- $(\tilde{x}_1, \tilde{y}_1), \ldots, (\tilde{x}_m, \tilde{y}_m)$: training patterns (known)
- $w_1, \ldots, w_n$: weights (learnt)
- $\hat{y}$: output (guessed)

phase I:

train network

phase II:

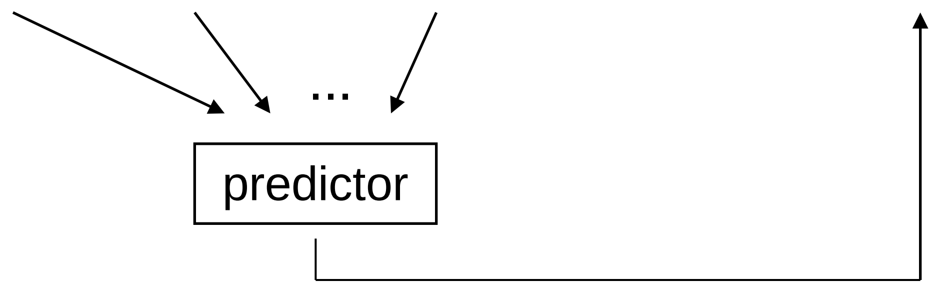
apply network to unkown inputs for classification

Prediction of Time Series

time series $x_1, x_2, x_3, \ldots$ (e.g. temperatures, exchange rates, ...)

task: given a subset of historical data, predict the future

$$f(x_{t-k}, x_{t-k+1}, \ldots, x_t; w_1, \ldots, w_n) \rightarrow \hat{x}_{t+\tau}$$



phase I:

train network

phase II:

apply network to historical inputs for predicting unkown outputs

training patterns:

historical data where true output is known;

error per pattern = $(\hat{x}_{t+\tau} - x_{t+\tau})^2$

Prediction of Time Series: Example for Creating Training Data

given: time series 10.5, 3.4, 5.6, 2.4, 5.9, 8.4, 3.9, 4.4, 1.7

time window: k=3

(10.5, 3.4, 5.6) 2.4

first input / output pair

known input

known output

further input / output pairs:

(3.4, 5.6, 2.4) 5.9

(5.6, 2.4, 5.9) 8.4

(2.4, 5.9, 8.4) 3.9

(5.9, 8.4, 3.9) 4.4

(8.4, 3.9, 4.4) 1.7

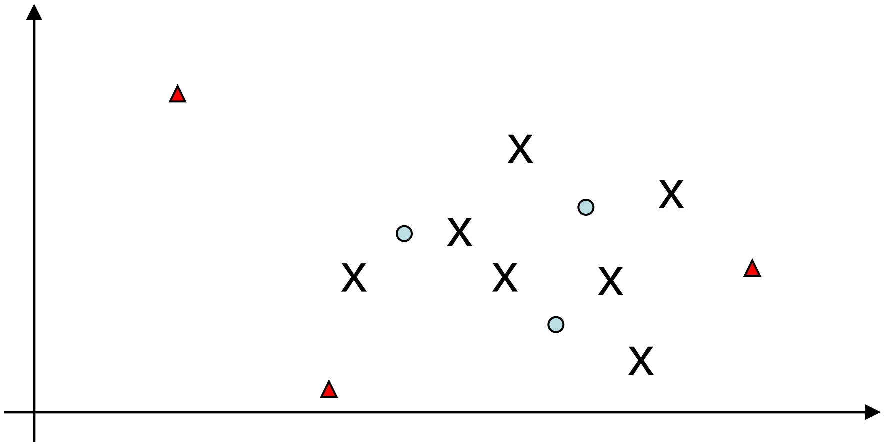
Function Approximation (the general case)

task: given training patterns (input / output), approximate unkown function

→ should give outputs close to true unkown function for arbitrary inputs

• values between training patterns are **interpolated**

• values outside convex hull of training patterns are **extrapolated**



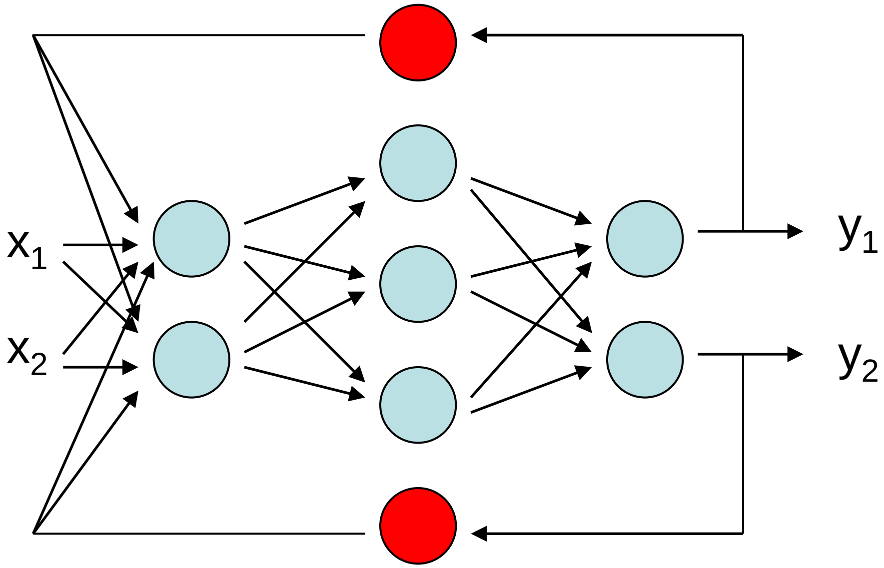
x : input training pattern

○ : input pattern where output to be interpolated

▲ : input pattern where output to be extrapolated

Jordan nets (1986)

- **context neuron**:
  reads output from some neuron at step t and feeds value into net at step t+1



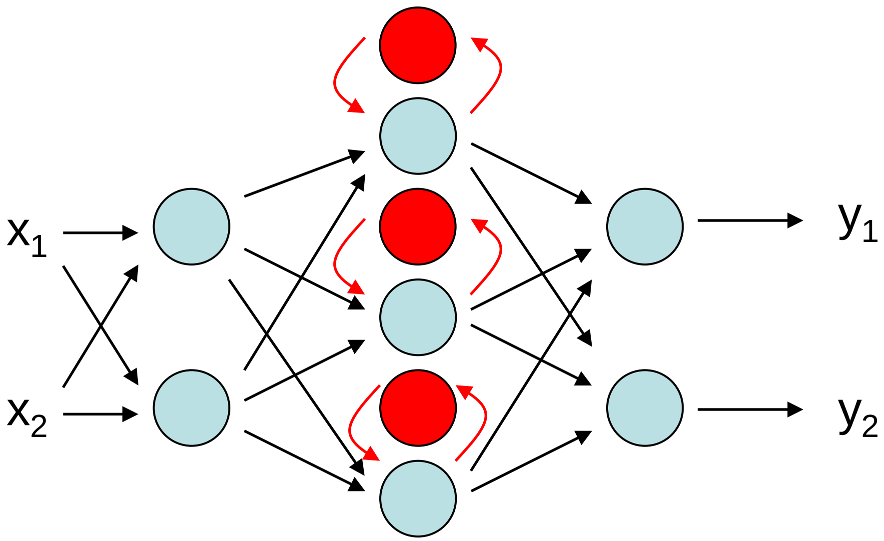
Jordan net =

MLP + context neuron for each output, context neurons fully connected to input layer

Elman nets (1990)

Elman net =

MLP + context neuron for each hidden layer neuron‘s output of MLP,
context neurons fully connected to emitting MLP layer



Training?

⇒ unfolding in time (“loop unrolling“)

- identical MLPs serially connected (finitely often)
- results in a large MLP with many hidden (inner) layers
- backpropagation may take a long time
- but reasonable if most recent past more important than layers far away

Why using backpropagation?

⇒ use *Evolutionary Algorithms* directly on recurrent MLP!

later!

Definition:

A function $\phi : \mathbb{R}^n \to \mathbb{R}$ is termed **radial basis function**

iff $\exists\ \varphi : \mathbb{R} \to \mathbb{R} : \forall\ x \in \mathbb{R}^n : \phi(x; c) = \varphi\ (\ \|\ x - c\ \|\ )$. □

Definition:

RBF **local** iff

$\varphi(r) \to 0$ as $r \to \infty$ □

typically, || x || denotes Euclidean norm of vector x

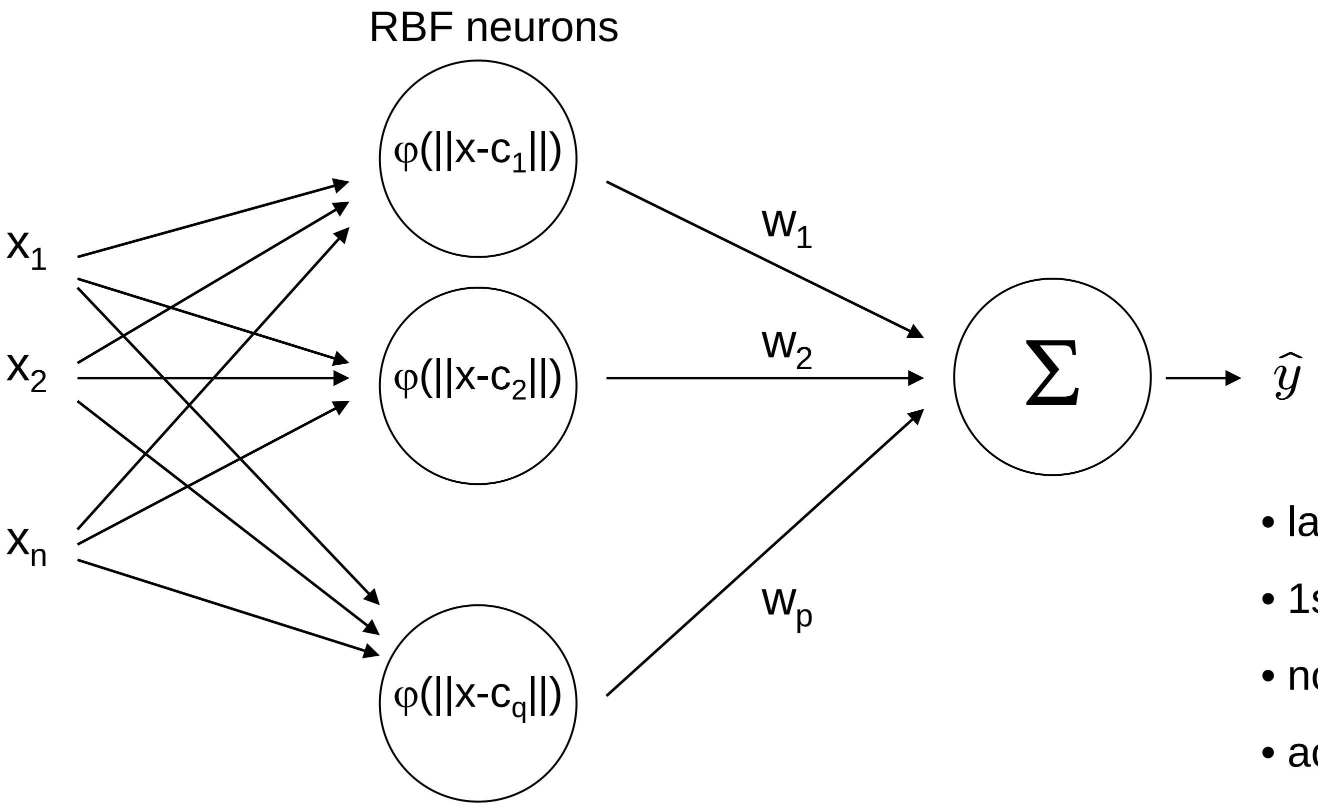
examples:

$\varphi(r) = \exp\left(-\frac{r^2}{\sigma^2}\right)$	Gaussian	unbounded	local
$\varphi(r) = \frac{3}{4}(1 - r^2) \cdot 1_{\{r \le 1\}}$	Epanechnikov	bounded	local
$\varphi(r) = \frac{\pi}{4} \cos\left(\frac{\pi}{2} r\right) \cdot 1_{\{r \le 1\}}$	Cosine	bounded	local

Definition:

A function f: $\mathbb{R}^n \rightarrow \mathbb{R}$ is termed **radial basis function net (RBF net)**

iff $f(x) = w_1\, \varphi(\| x - c_1 \|) + w_2\, \varphi(\| x - c_2 \|) + \ldots + w_p\, \varphi(\| x - c_q \|)$ □



- layered net
- 1st layer fully connected
- no weights in 1st layer
- activation functions differ

given : N training patterns (x_i, y_i) and q RBF neurons

find : weights $w_1, \ldots, w_q$ with minimal error

solution:

we know that $f(x_i) = y_i$ for $i = 1, \ldots, N$ and therefore we insist that

$$\sum_{k=1}^{q} w_k \cdot \underbrace{\varphi(\|x_i - c_k\|)}_{p_{ik}} = y_i$$

w_k: unknown p_{ik}: known value y_i: known value

$$\Rightarrow \quad \sum_{k=1}^{q} w_k \cdot p_{ik} = y_i$$

$\Rightarrow$ N linear equations with q unknowns

in matrix form: $P w = y$ with $P = (p_{ik})$ and P: $N \times q$, y: $N \times 1$, w: $q \times 1$,

case $N = q$: $w = P^{-1} y$ if P has full rank

case $N < q$: many solutions but of no practical relevance

case $N > q$: $w = P^{+} y$ where P^{+} is Moore-Penrose pseudo inverse

$P w = y$ | $\cdot$ P' from left hand side (P' is transpose of P)

$P'P w = P' y$ | $\cdot$ $(P'P)^{-1}$ from left hand side

$\underbrace{(P'P)^{-1} P'P}_{\text{unit matrix}} w = \underbrace{(P'P)^{-1} P'}_{P^{+}} y$ | simplify

complexity (naive)

$w = (P'P)^{-1} P' y$

$P'P$: $N^2 q$ inversion: q^3 $P'y$: qN multiplication: q^2

$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}$

$O(N^2 q)$

remark: if N large then inaccuracies for P'P likely

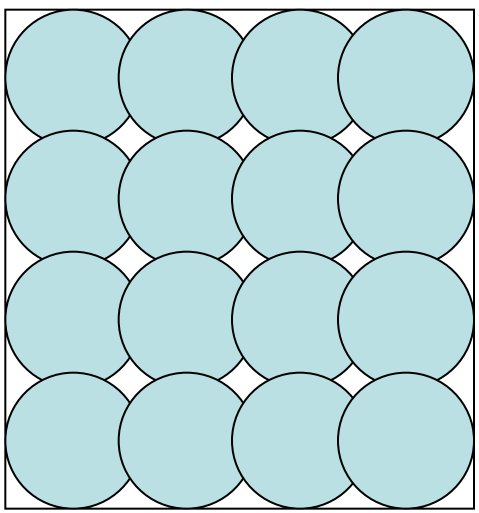
⇒ first analytic solution, then gradient descent starting from this solution

(gradient descent) requires differentiable basis functions!

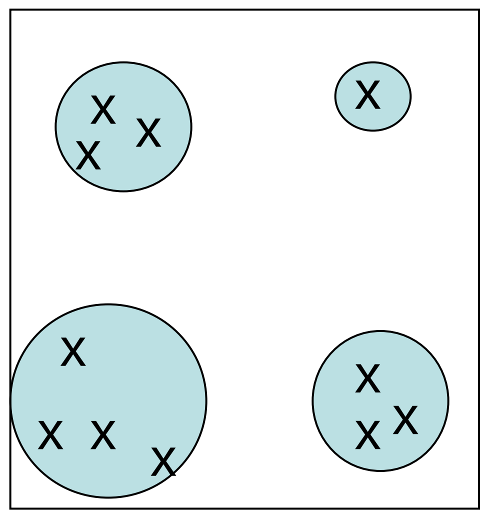
so far: tacitly assumed that RBF neurons are given

⇒ center c_k and radii σ considered given and known

how to choose c_k and σ ?



uniform covering



if training patterns inhomogenously distributed then first cluster analysis

choose center of basis function from each cluster, use cluster size for setting σ

advantages:

- additional training patterns → only local adjustment of weights
- optimal weights determinable in polynomial time
- regions not supported by RBF net can be identified by zero outputs

  (if output close to zero, verify that output of each basis function is close to zero)

disadvantages:

- number of neurons increases exponentially with input dimension
- unable to extrapolate (since there are no centers and RBFs are local)