Artificial Neural Networks and Applications

Systems Modeling and Control Using Dynamic Neural Networks and Fuzzy-Neural Networks

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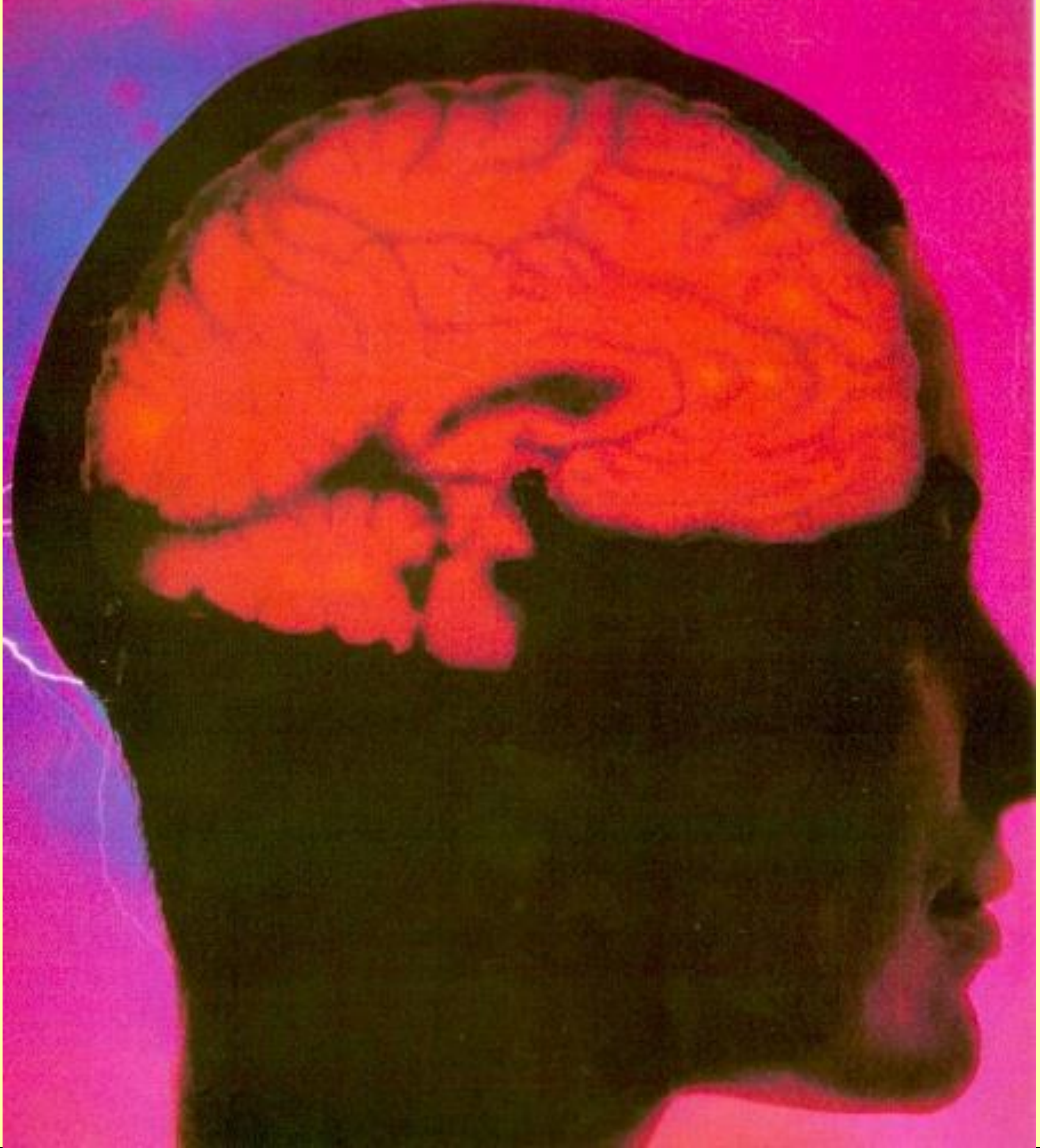
ENGINEERING INTELLIGENCE



The Human Being is Intelligent

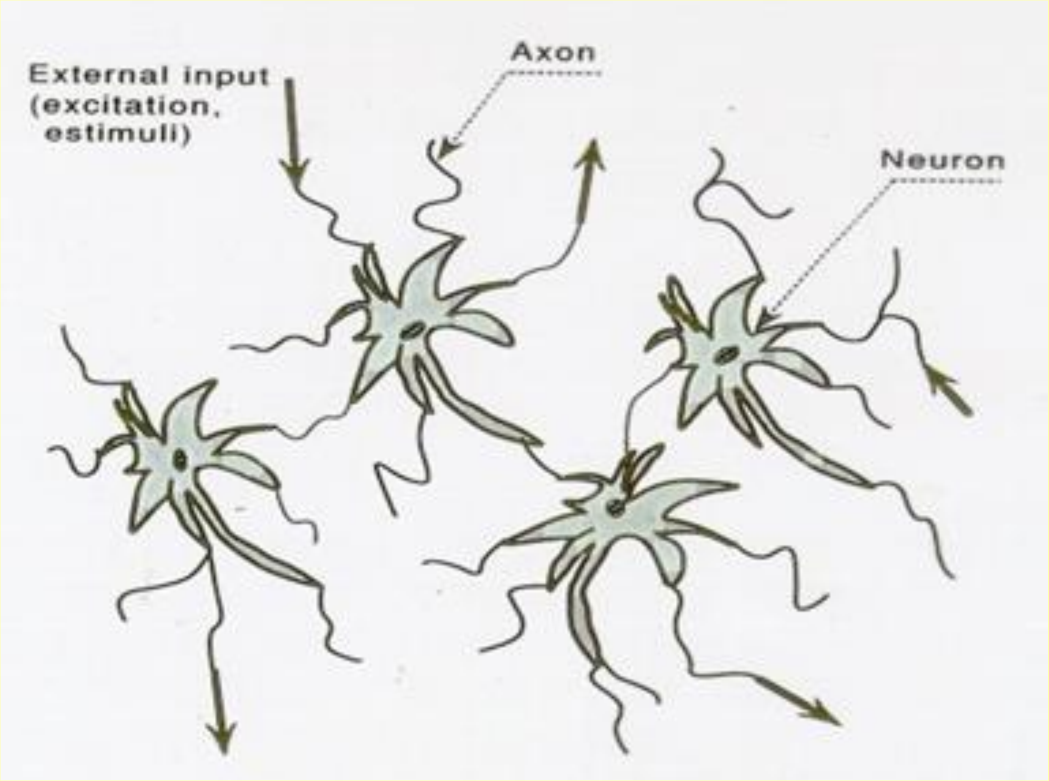
It has the capacity for:

- Thinking
- Reasoning
- Learning
- Improving
- Adapting
- ....

Able to Work in an Autonomous Way

The Brain

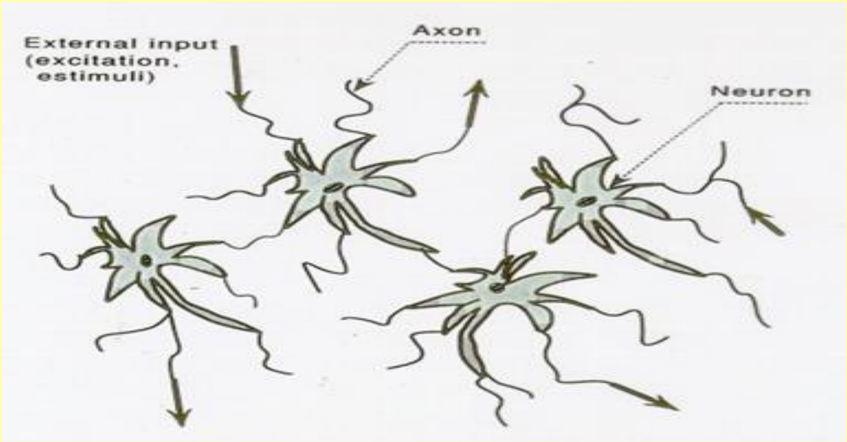
A Natural Neural Network

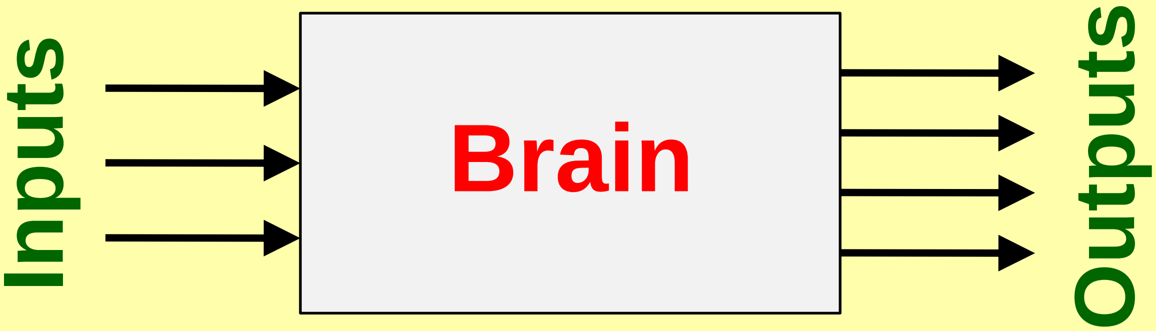


Millons of highly interconnected neurons

The Brain

Behaves as a System with Inputs and Outputs

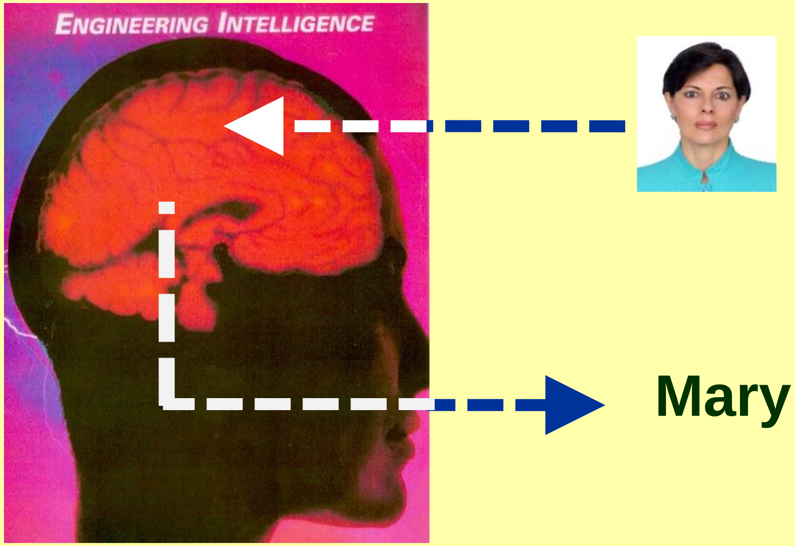


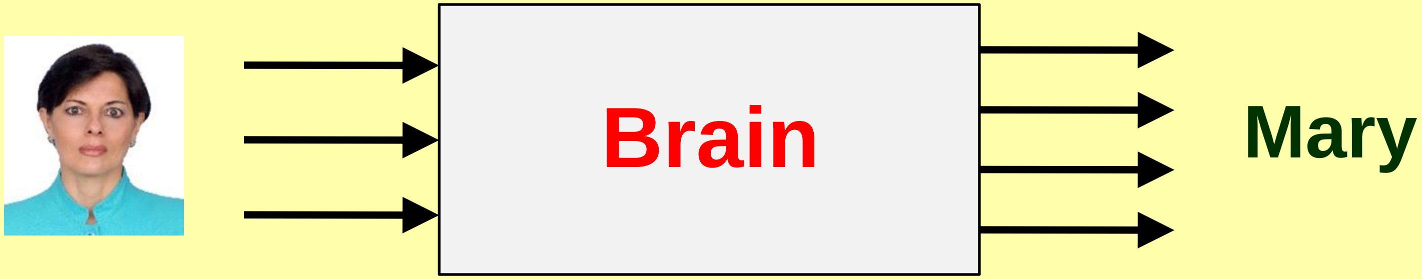


Face Recognition

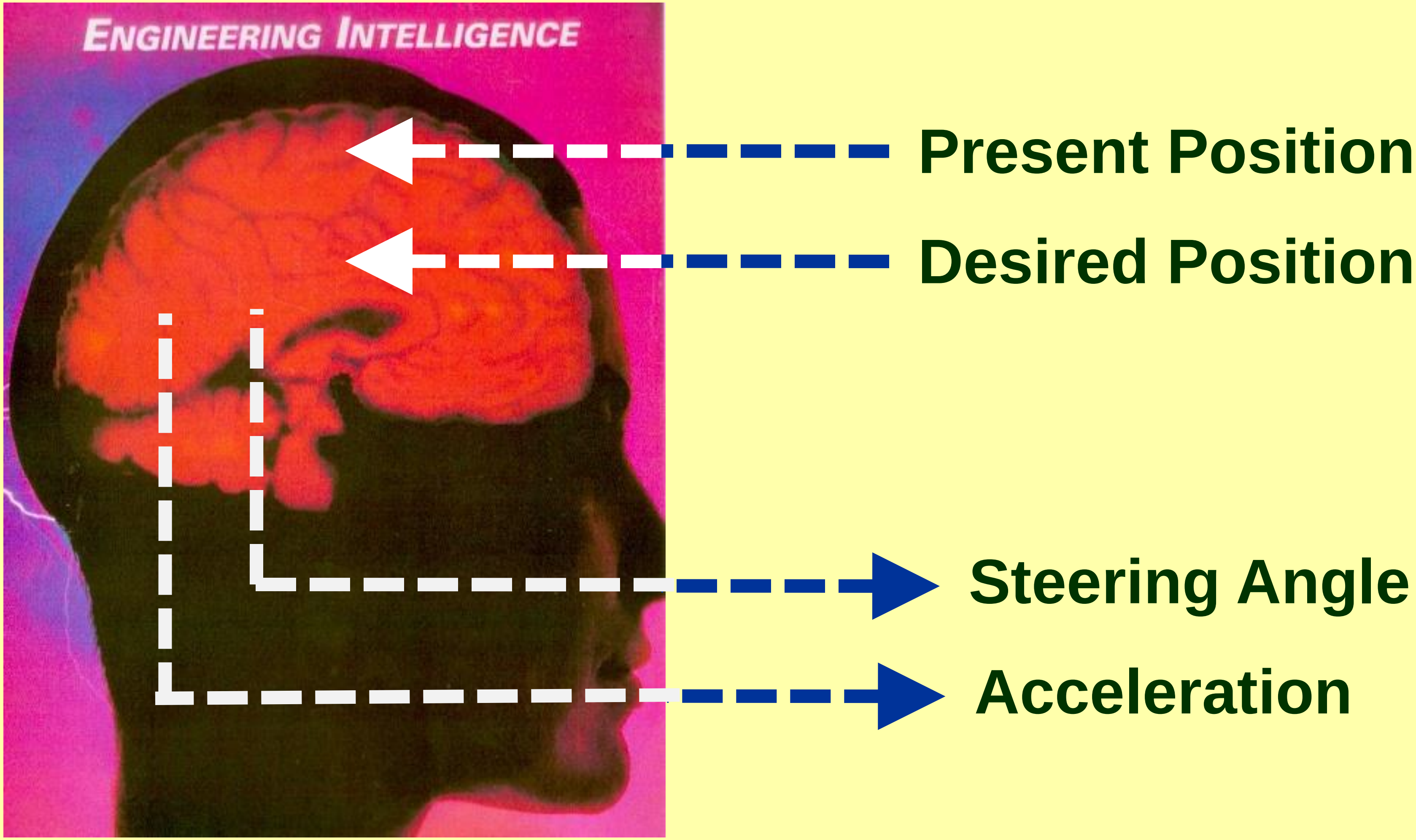
Mary

Face Recognition

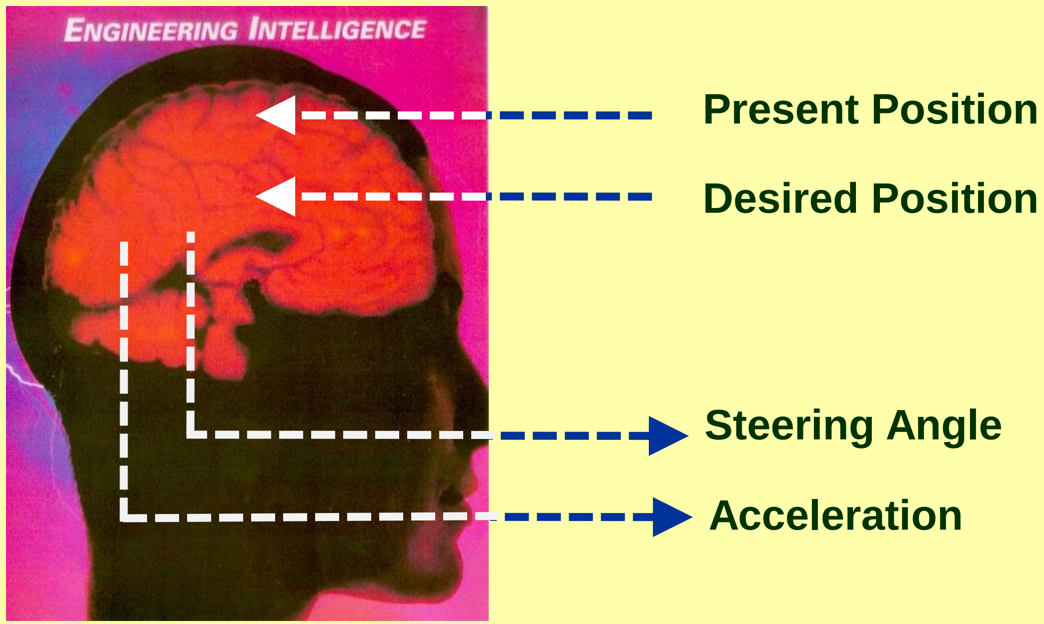


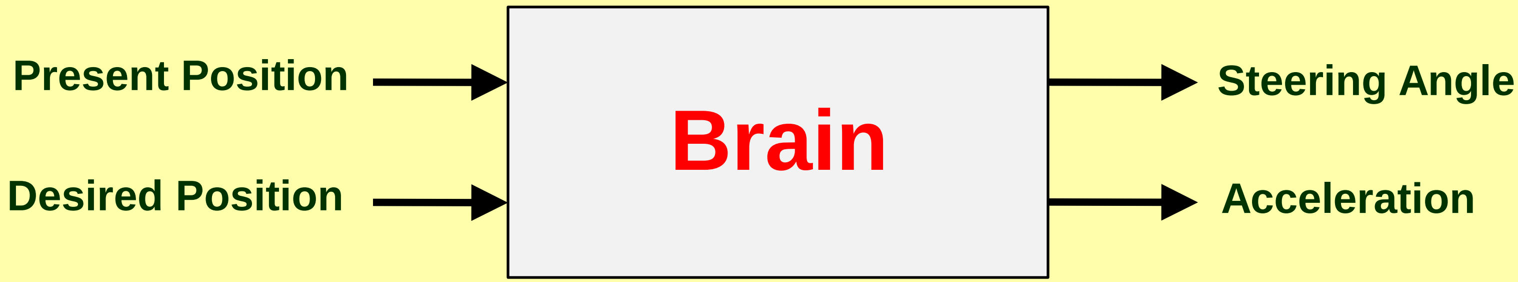


Car Driving


ENGINEERING INTELLIGENCE
Present Position
Desired Position
Steering Angle
Acceleration

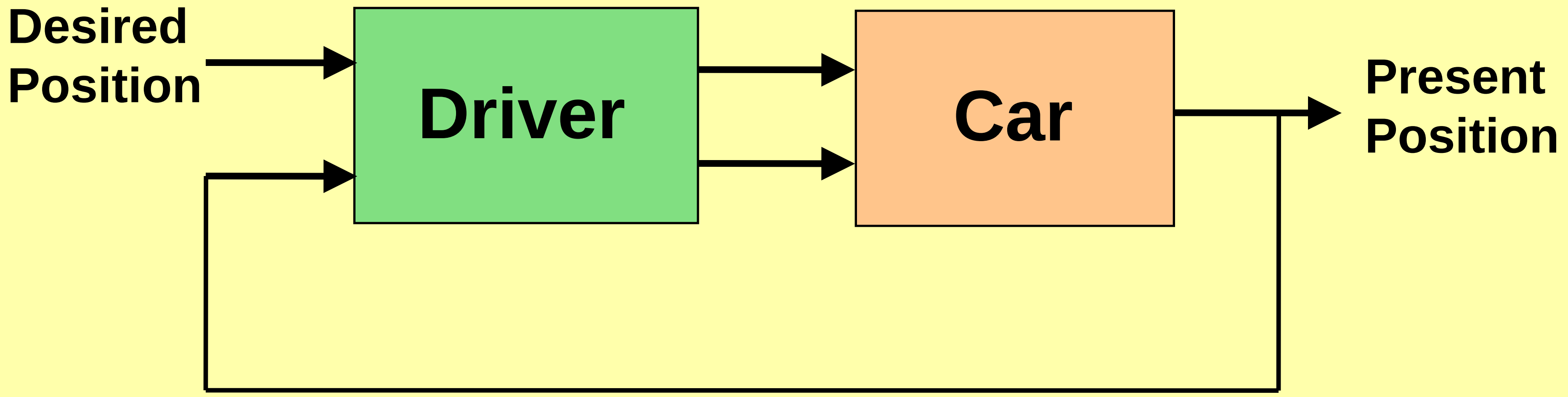
Car Driving


ENGINEERING INTELLIGENCE
Present Position
Desired Position
Steering Angle
Acceleration

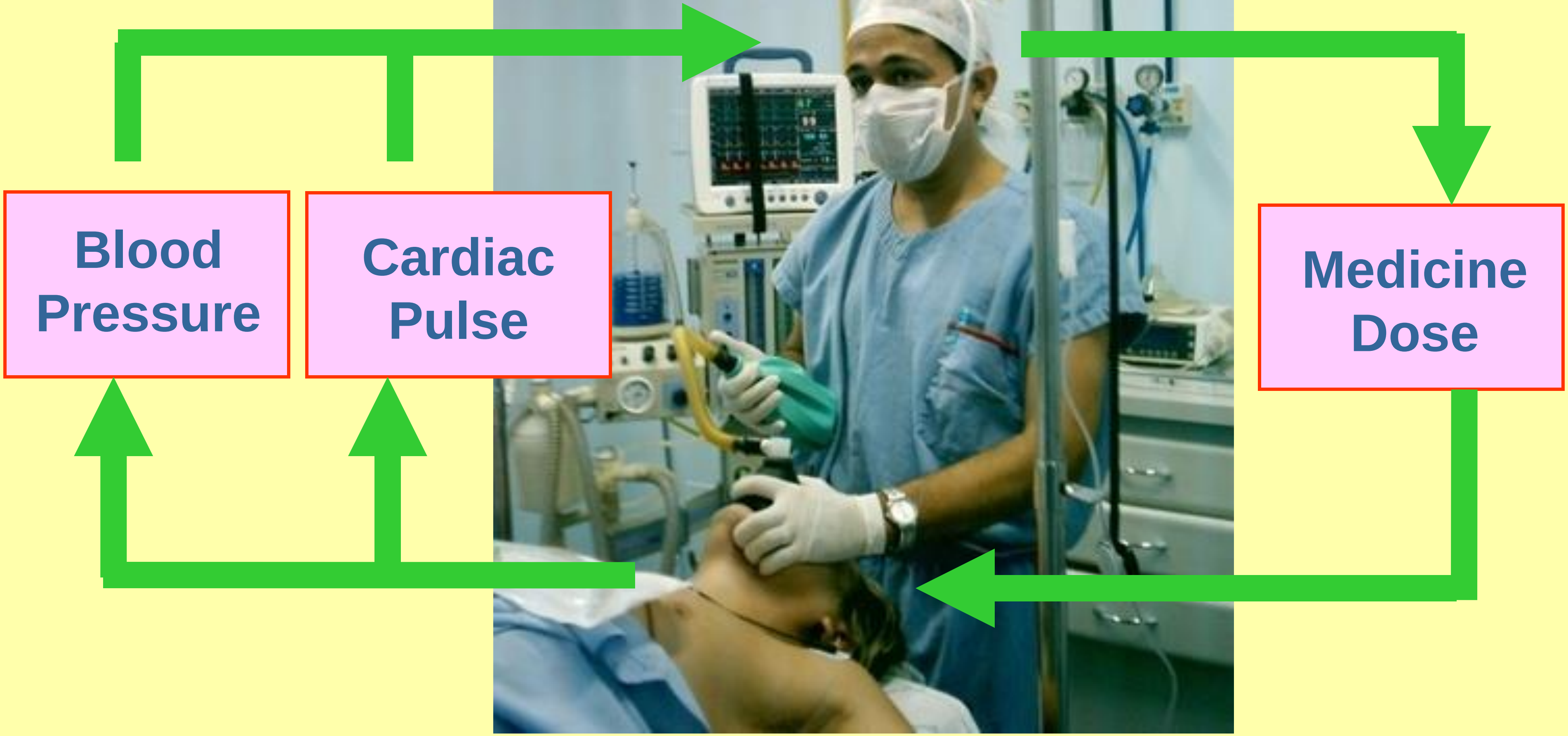

Present Position
Desired Position
Brain
Steering Angle
Acceleration

Car Driving

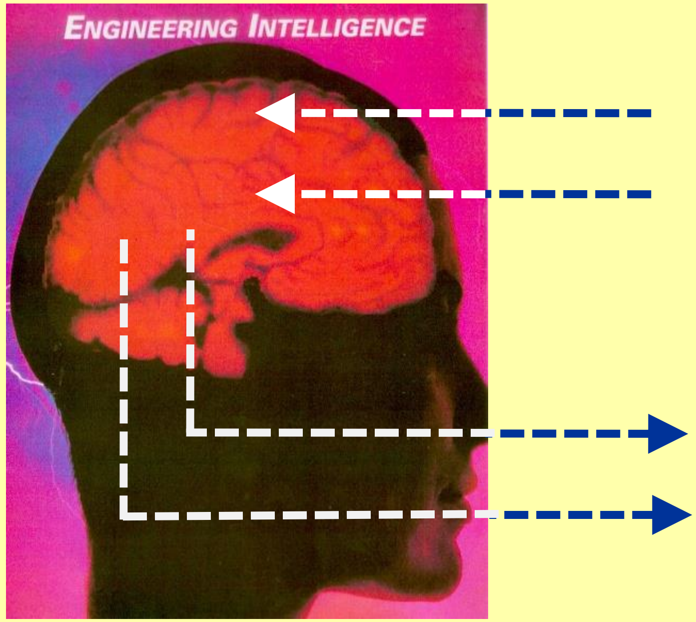
A Control Problem

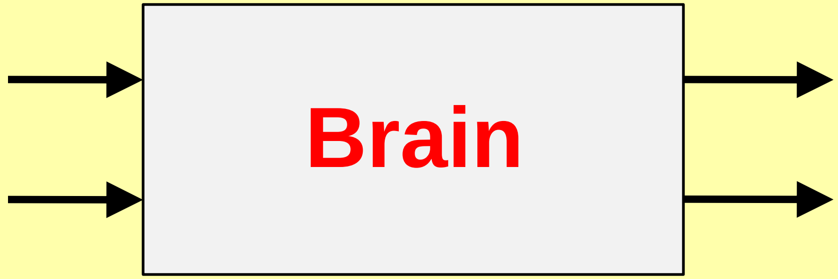


Medical Treatment



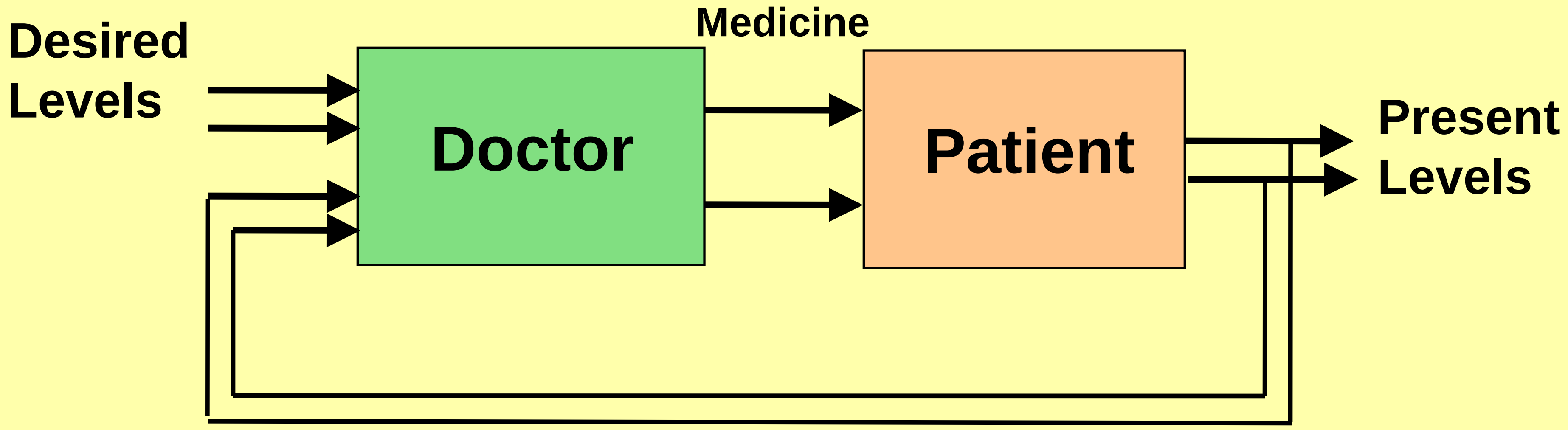
Medical Treatment





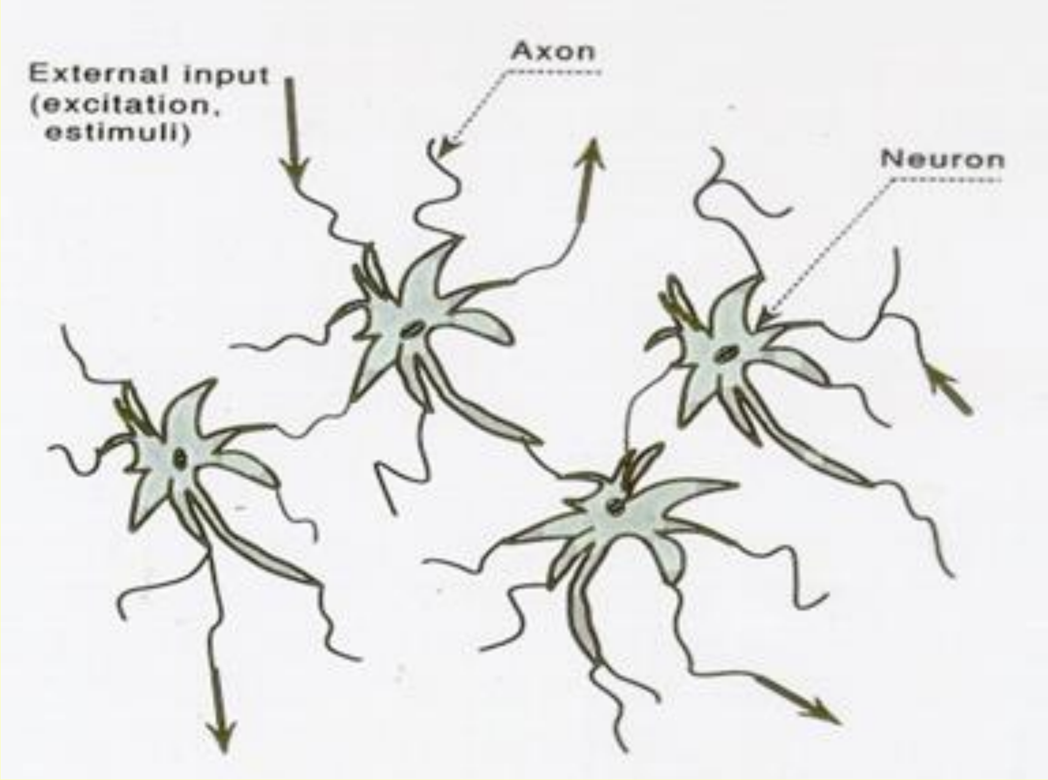
Medical Treatment

A Control Problem



The Brain

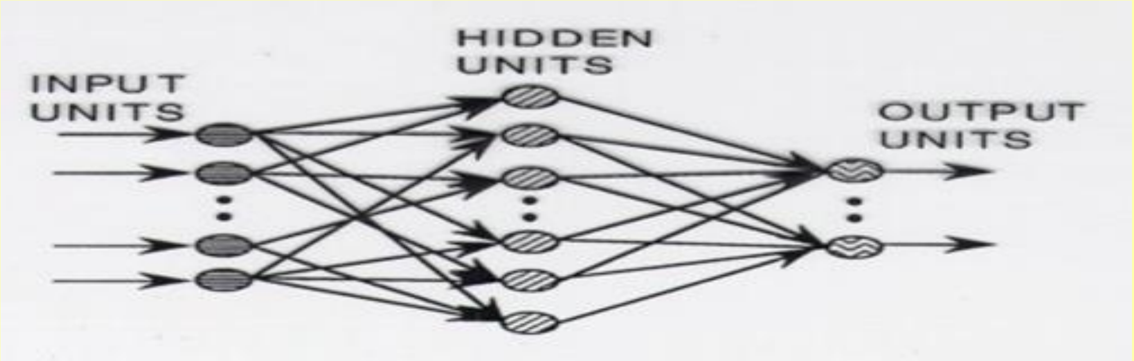
A Natural Neural Network



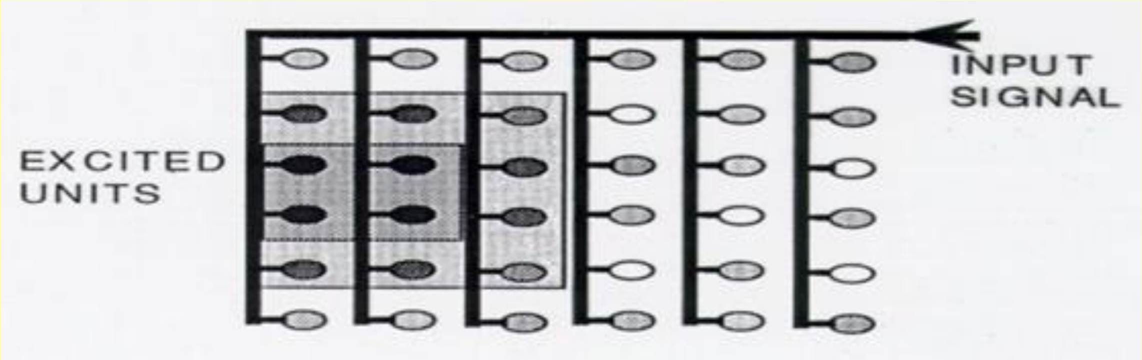
Millons of highly interconnected neurons

Artificial Neural Network Models

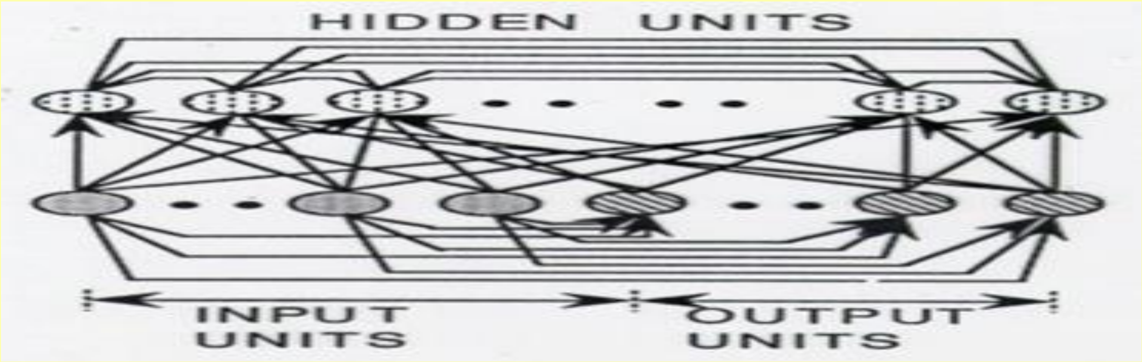
Multilayer Neural Network



Self-Organizing Map

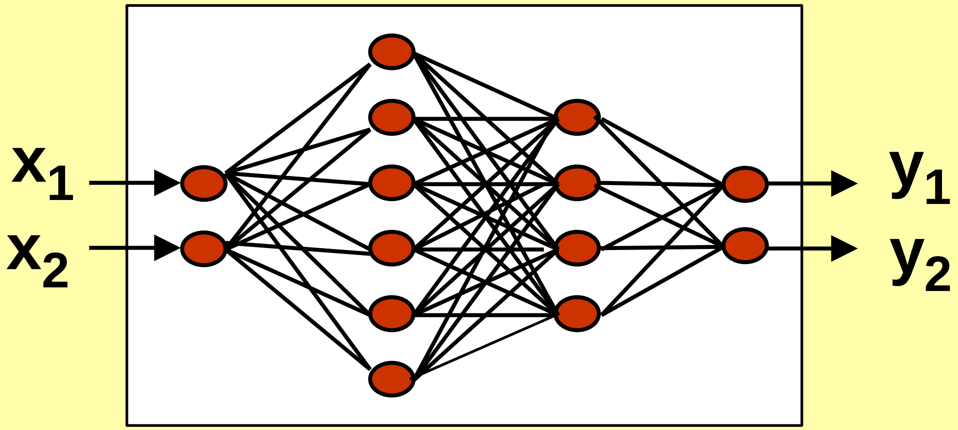


Boltzmann Completion Network

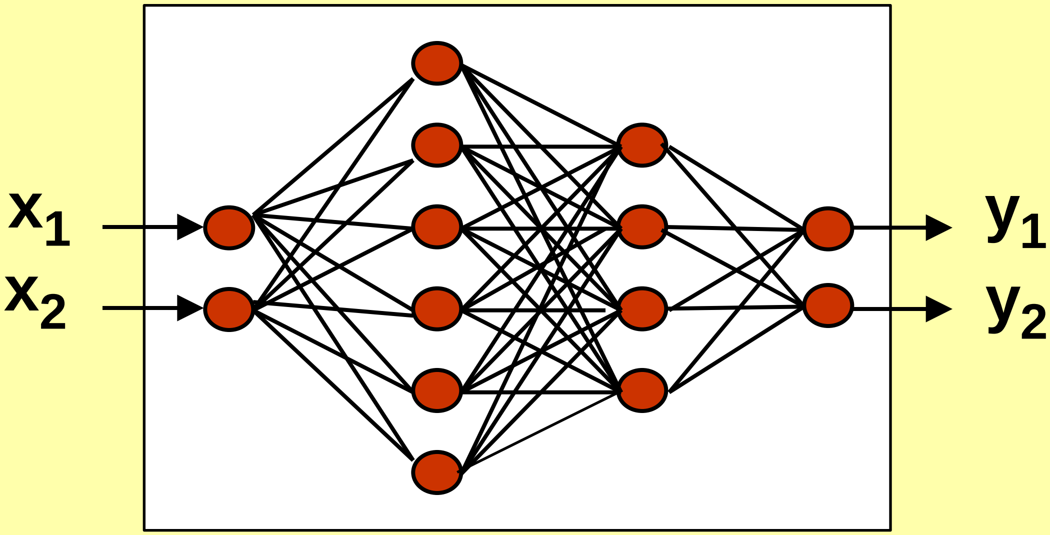


Neural Networks

Systems capable of estimating functions of several inputs and outputs using input-output data

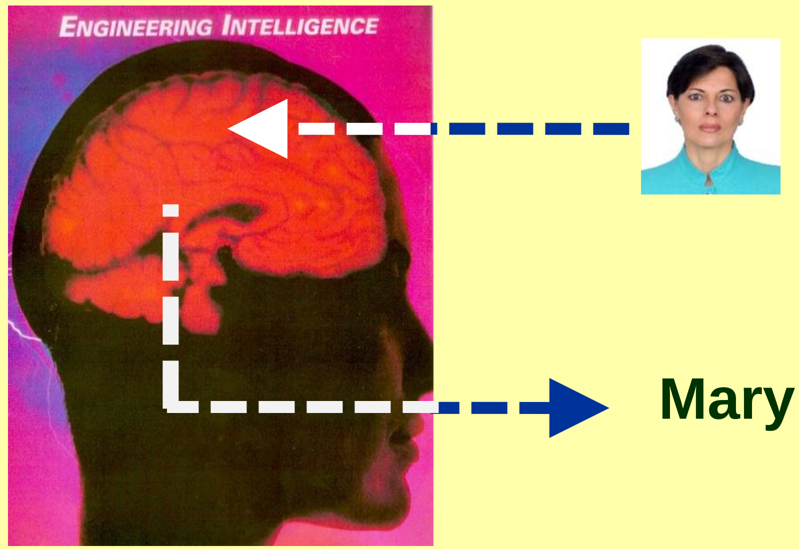


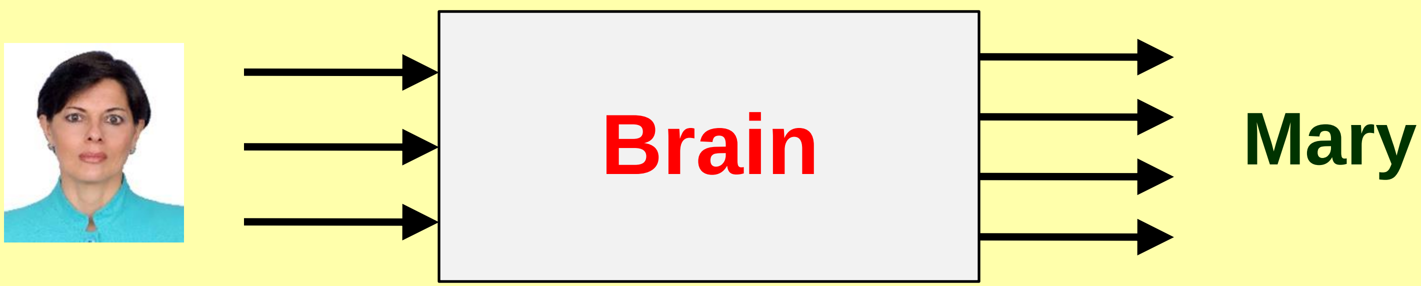
Neural Networks



$$y = \Phi(x)$$

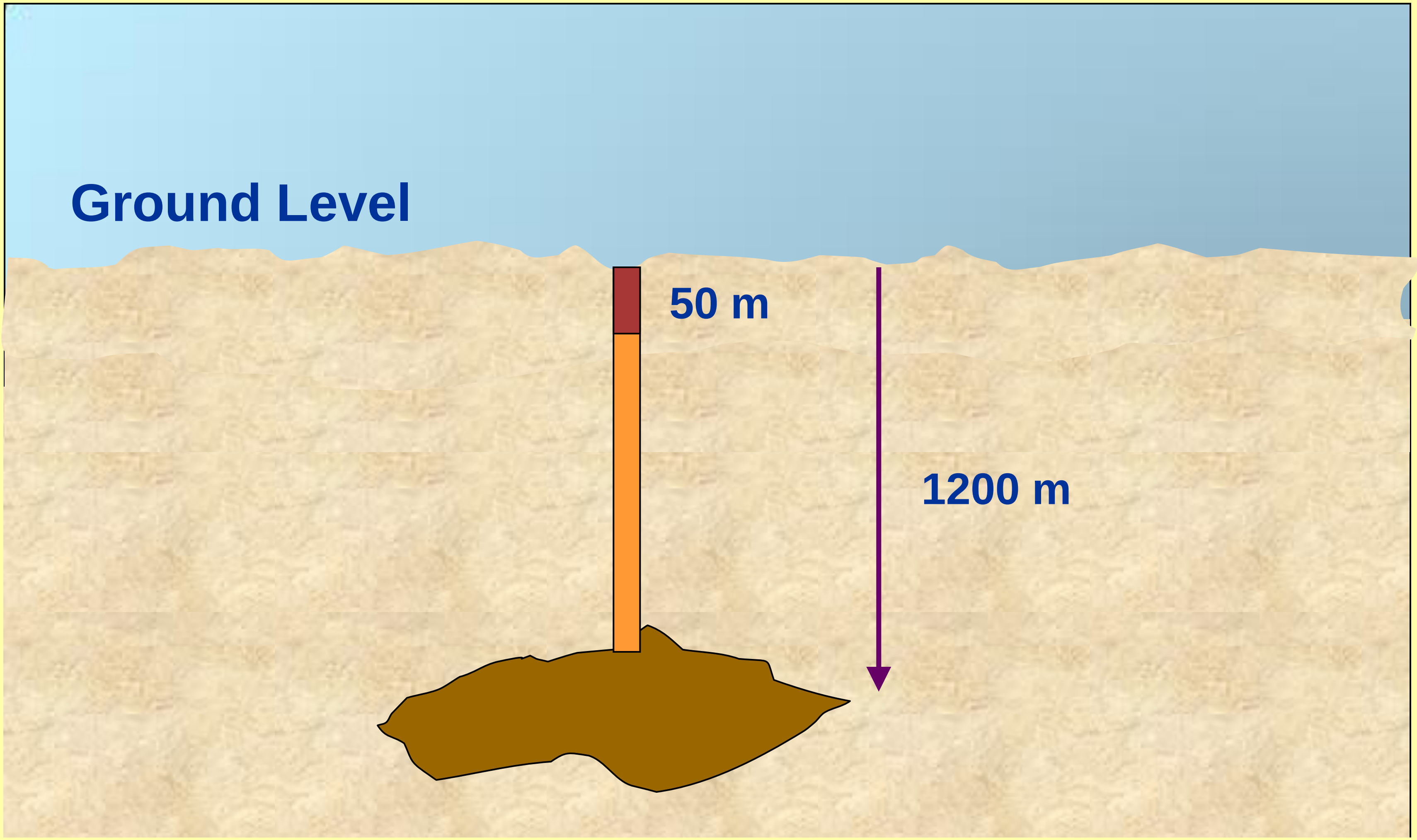
Face Recognition





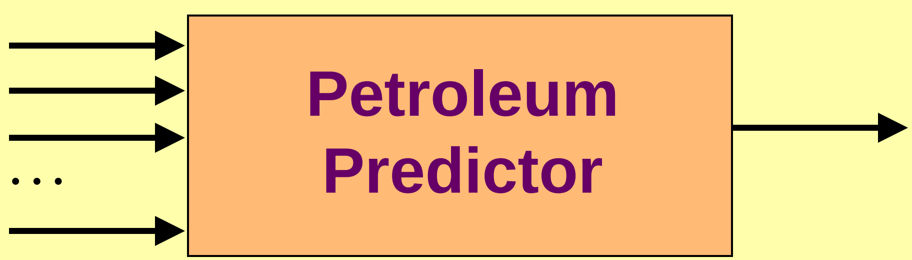
$$y = \Phi(x)$$

Petroleum Prediction

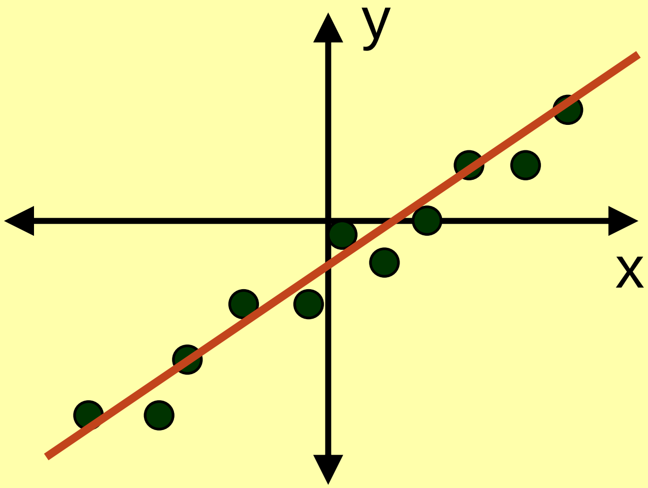


Petroleum Prediction

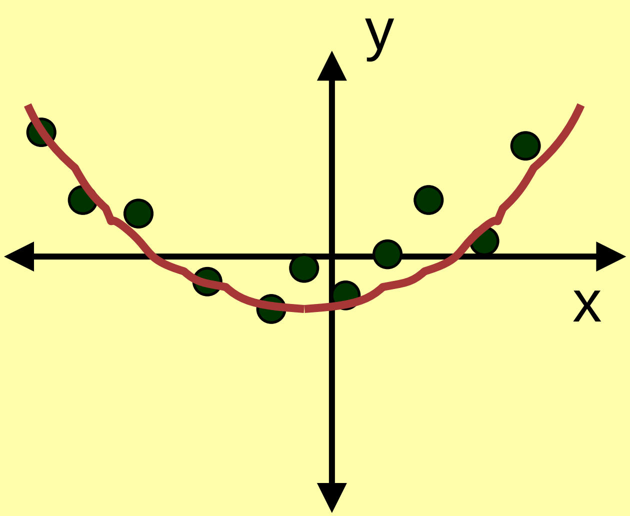
	10m				...... 50m				
	Tem	Hum	Ca	Su	Tem	Hum	Ca	Su	Petroleum
Well 1	42	55	14	2	56	42	12	1	1
Well 2	39	62	20	4	54	40	18	1	0
Well 3	33	31	36	1	51	40	31	2	0
.. ..		.. ..		.. ..		.. ..			.. ..
Well 50	45	51	19	5	60	48	21	3	1



Function Estimation



$$y = ax + b$$

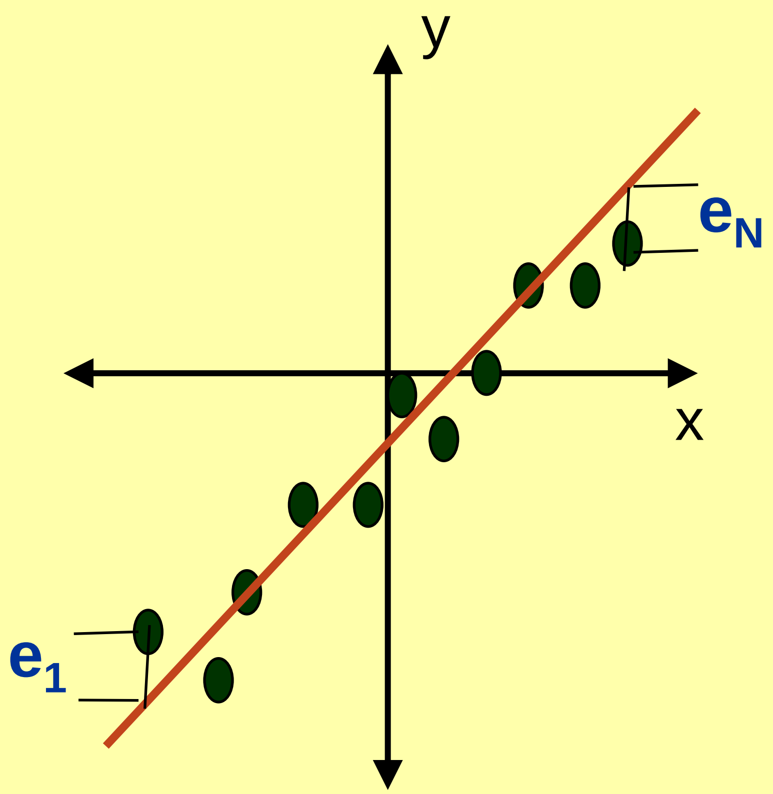


$$y = ax^2 + bx + c$$

Function Estimation

Data

x	$\bar{y}$
x_1	$\bar{y}_1$
x_2	$\bar{y}_2$
x_3	$\bar{y}_3$
⋮	⋮
x_N	$\bar{y}_N$



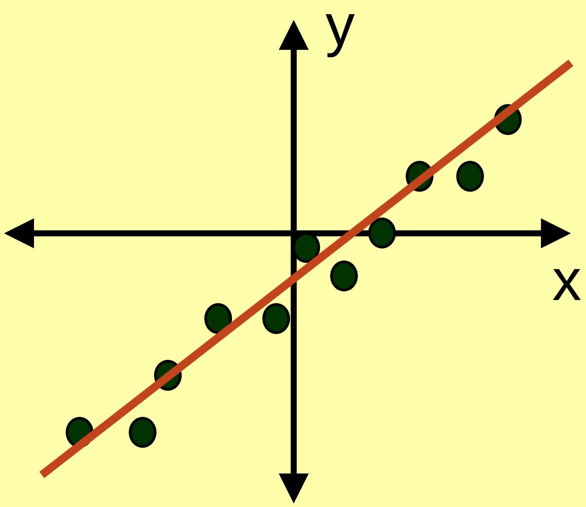
$$y = ax + b$$

Sum of Errors Squares

$$J = 0.5\, e_1^2 + 0.5\, e_2^2 + \cdots + 0.5\, e_N^2$$

$$J = 0.5\, (y_1 - \bar{y}_1)^2 + 0.5\, (y_2 - \bar{y}_2)^2 + \cdots + 0.5\, (y_N - \bar{y}_N)^2$$

Function Estimation



$$y = ax + b$$

$$J = 0.5\,(y_1-\bar{y}_1)^2 + 0.5\,(y_2-\bar{y}_2)^2 + \cdots\cdots + 0.5\,(y_N-\bar{y}_N)^2$$

Problem: Find a and b that minimize J

Function Estimation

$$y = ax + b$$

$$J = 0.5\,(y_1-\overline{y}_1)^2 + 0.5\,(y_2-\overline{y}_2)^2 + \cdots\cdots + 0.5\,(y_N-\overline{y}_N)^2$$

Problem: Find a and b that minimize J

Solution

Exact Method:

$$\frac{\partial J}{\partial a} = 0 \qquad \frac{\partial J}{\partial b} = 0$$

Iterative Method:

$$a = a - \eta\frac{\partial J}{\partial a} \qquad b = b - \eta\frac{\partial J}{\partial b}$$

Function Estimation

Iterative Method

$$a = a - \eta \frac{\partial J}{\partial a} \qquad b = b - \eta \frac{\partial J}{\partial b}$$

η : Learning rate

Fix value of η

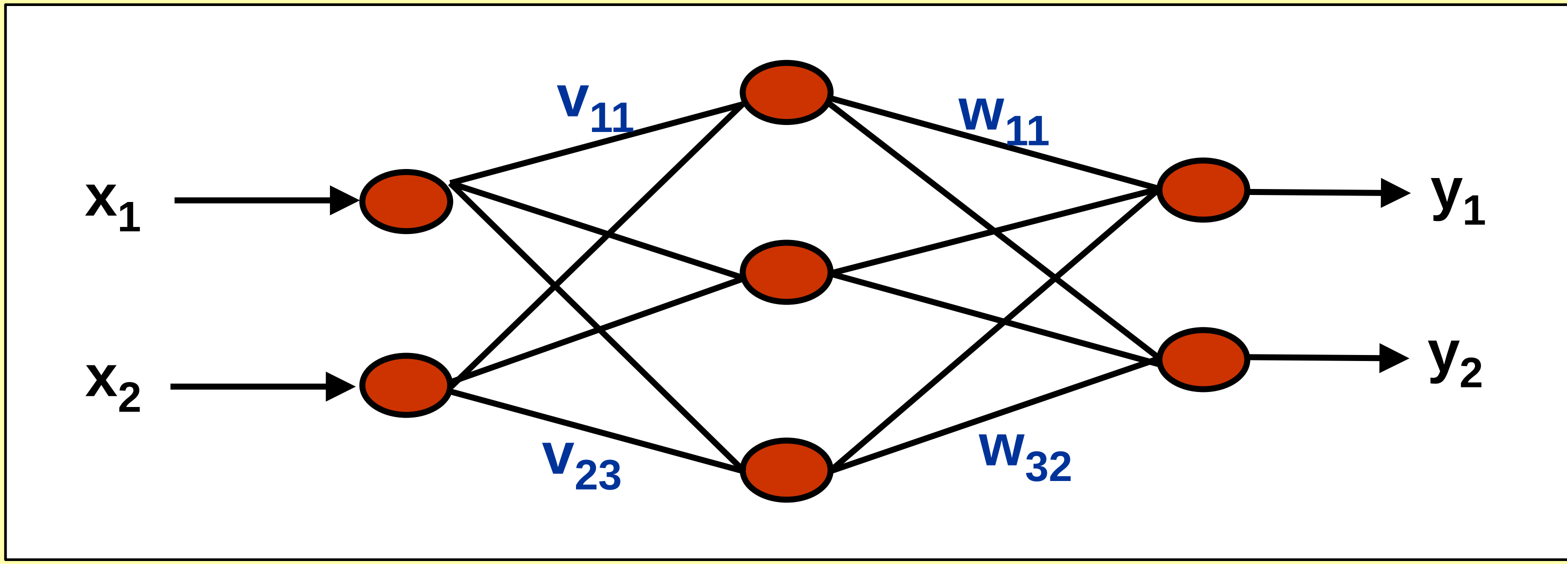
Initial values of a and b

Compute derivatives $\partial J/\partial a$ and $\partial J/\partial b$

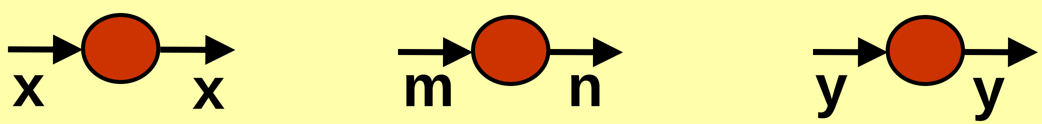
Update a and b

Verify convergence condition

Neural Network



Input Layer	Hidden Layer	Output Layer

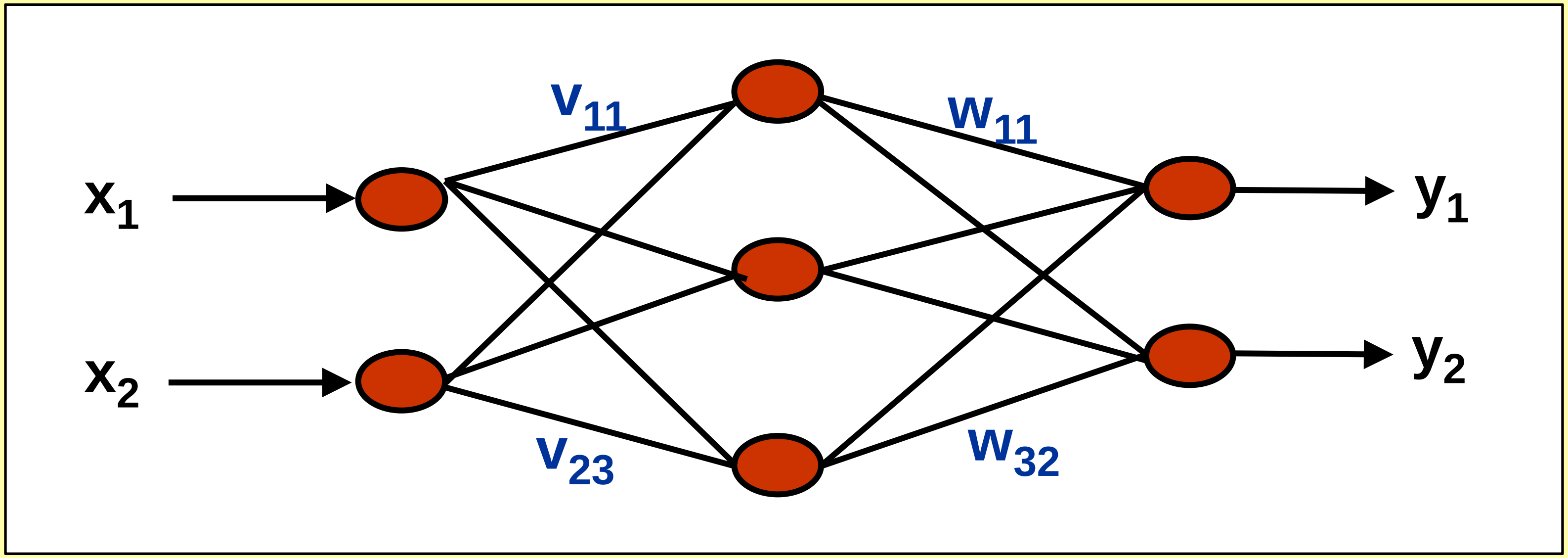


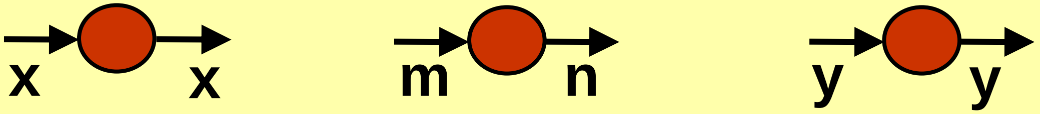
Linear	Non-Linear	Linear

v_{11} ..... v_{23}
w_{11} ..... w_{32}

Weights, Connection Coefficients

Neural Network





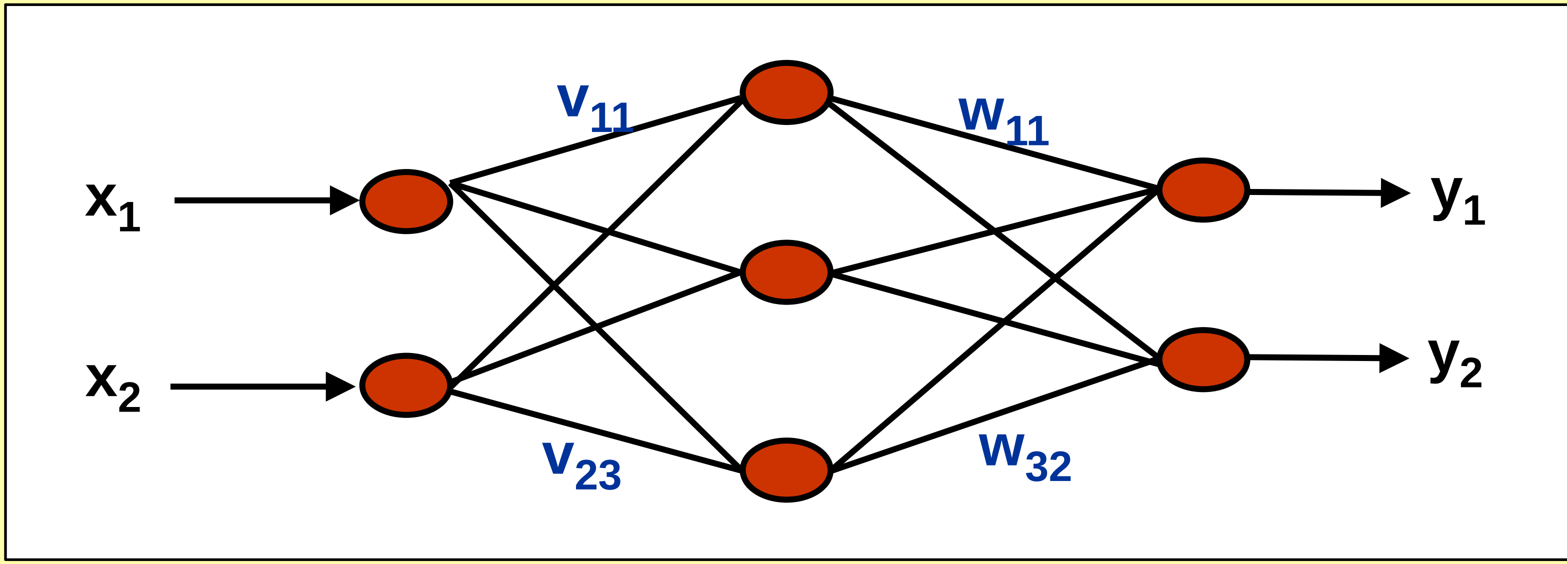
Linear **Non-Linear** **Linear**

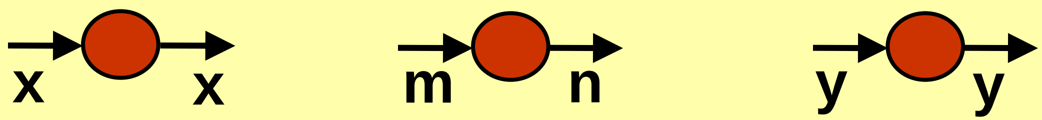
Sigmoid $$n = \frac{1}{1 + e^{-m}}$$

$$n = f(m)$$

Gaussian $$n = e^{-m^2}$$

Neural Network





$$m_1 = v_{11}\, x_1 + v_{21}\, x_2$$
$$m_2 = v_{12}\, x_1 + v_{22}\, x_2$$
$$m_3 = v_{13}\, x_1 + v_{23}\, x_2$$

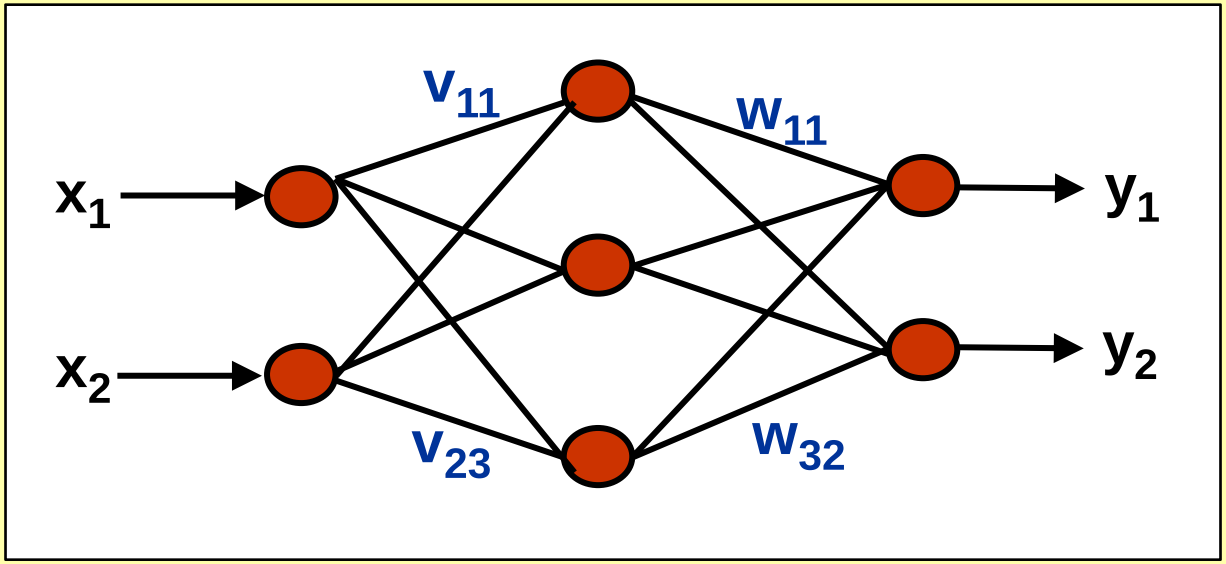
$$n_1 = f(m_1)$$
$$n_2 = f(m_2)$$
$$n_3 = f(m_3)$$

$$y_1 = w_{11}n_1 + w_{21}n_2 + w_{31}n_3$$
$$y_2 = w_{12}n_1 + w_{22}n_2 + w_{32}n_3$$

Training of Neural Network

Data

x_1	x_2	$\bar{y}_1$	$\bar{y}_2$
*	*	*	*
*	*	*	*
*	*	*	*
*	*	*	*

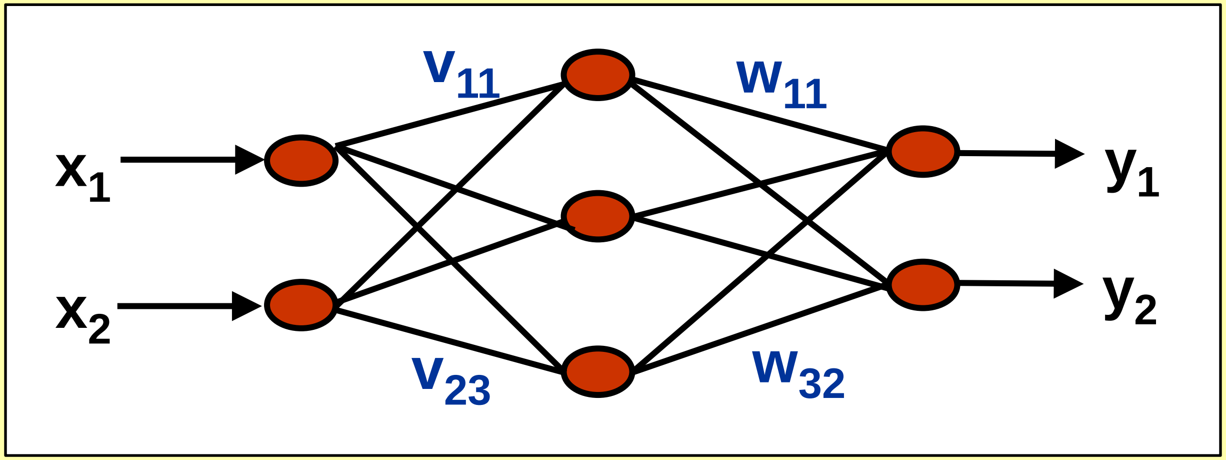


Cost function to be minimized:

$$J = 0.5\,(y_{(1)}-\bar{y}_{(1)})^T(y_{(1)}-\bar{y}_{(1)}) + \cdots\cdots + 0.5\,(y_{(N)}-\bar{y}_{(N)})^T\,(y_{(N)}-\bar{y}_{(N)})$$

$$y_{(k)} = [\ y_{1(k)} \quad y_{2(k)}\ ]^T$$

Training of Neural Network



$$J = 0.5\,(y_{(1)}-\bar{y}_{(1)})^T(y_{(1)}-\bar{y}_{(1)}) + \cdots\cdots + 0.5\,(y_{(N)}-\bar{y}_{(N)})^T\,(y_{(N)}-\bar{y}_{(N)})$$

Problem

Find $v_{11}\ \cdots\cdots\ v_{23}$ that minimize J

$w_{11}\ \cdots\cdots\ w_{32}$

Training of Neural Network

$$J = 0.5\,(y_{(1)}-\bar{y}_{(1)})^T(y_{(1)}-\bar{y}_{(1)}) + \cdots\cdots + 0.5\,(y_{(N)}-\bar{y}_{(N)})^T\,(y_{(N)}-\bar{y}_{(N)})$$

Problem

Find $v_{11}\ \cdots\cdots\ v_{23}$, $w_{11}\ \cdots\cdots\ w_{32}$ **that minimize J**

Iterative Method

$$v_{ij} = v_{ij} - \eta\,\frac{\partial J}{\partial v_{ij}}$$

$$w_{jk} = w_{jk} - \eta\,\frac{\partial J}{\partial w_{jk}}$$

$i = 1, 2$

$j = 1, 2, 3$

$k = 1, 2$

Training of Neural Network

$$J = 0.5\,(y_{(1)}-\bar{y}_{(1)})^T(y_{(1)}-\bar{y}_{(1)}) + \cdots\cdots + 0.5\,(y_{(N)}-\bar{y}_{(N)})^T\,(y_{(N)}-\bar{y}_{(N)})$$

Iterative Method

$$v_{ij} = v_{ij} - \eta \frac{\partial J}{\partial v_{ij}} \qquad w_{jk} = w_{jk} - \eta \frac{\partial J}{\partial w_{jk}}$$

Fix value of η

Initial values of v_{ij} and w_{jk}

Compute derivatives $\partial J/\partial v_{ij}$ and $\partial J/\partial w_{jk}$

Update v_{ij} and w_{jk}

Verify convergence condition

Training of Neural Network

How to compute the derivatives

$$\frac{\partial J}{\partial v_{ij}} \qquad \frac{\partial J}{\partial w_{jk}}$$

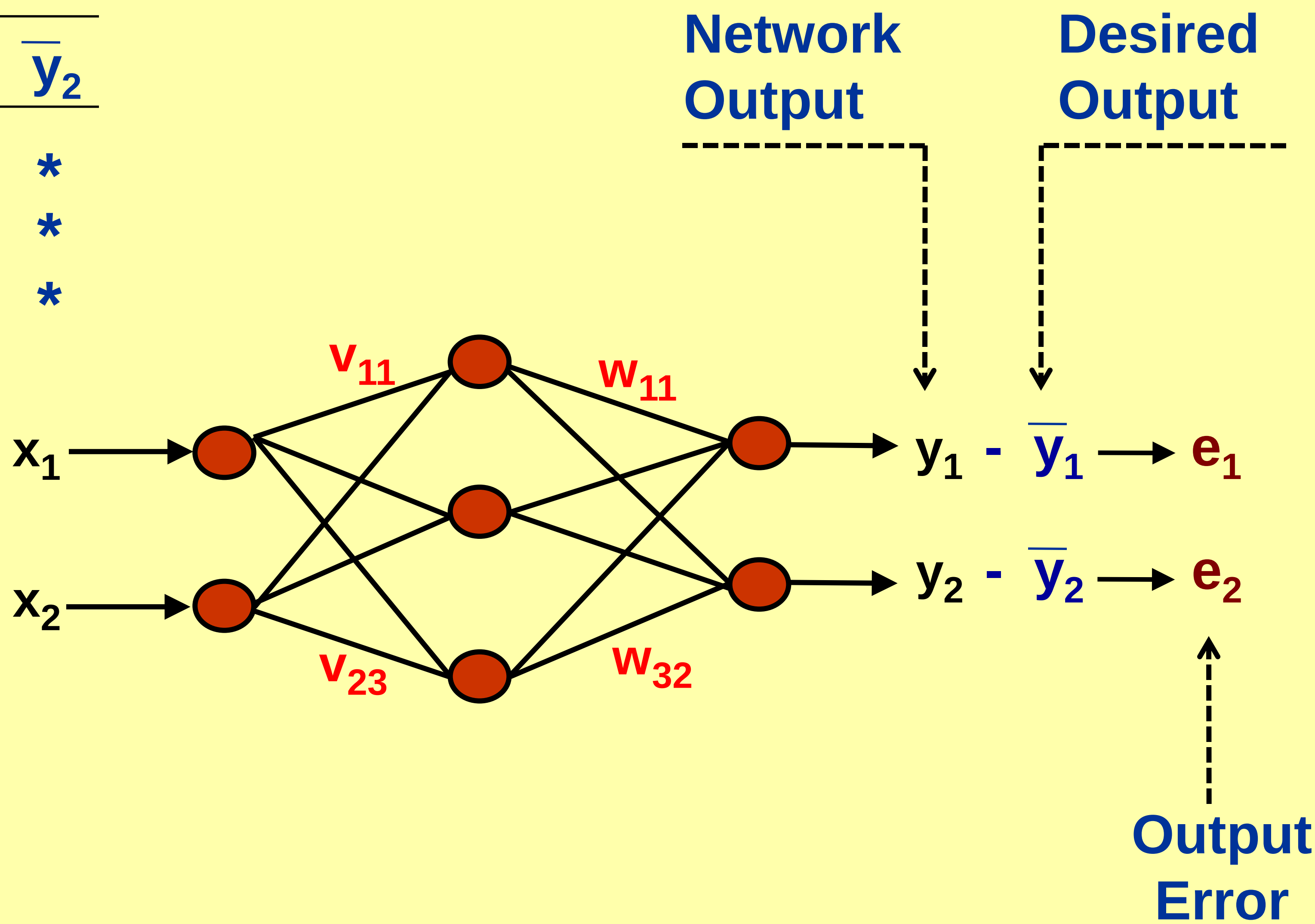
$\Rightarrow$ **Error Back Propagation Algorithm**

Delta Rule

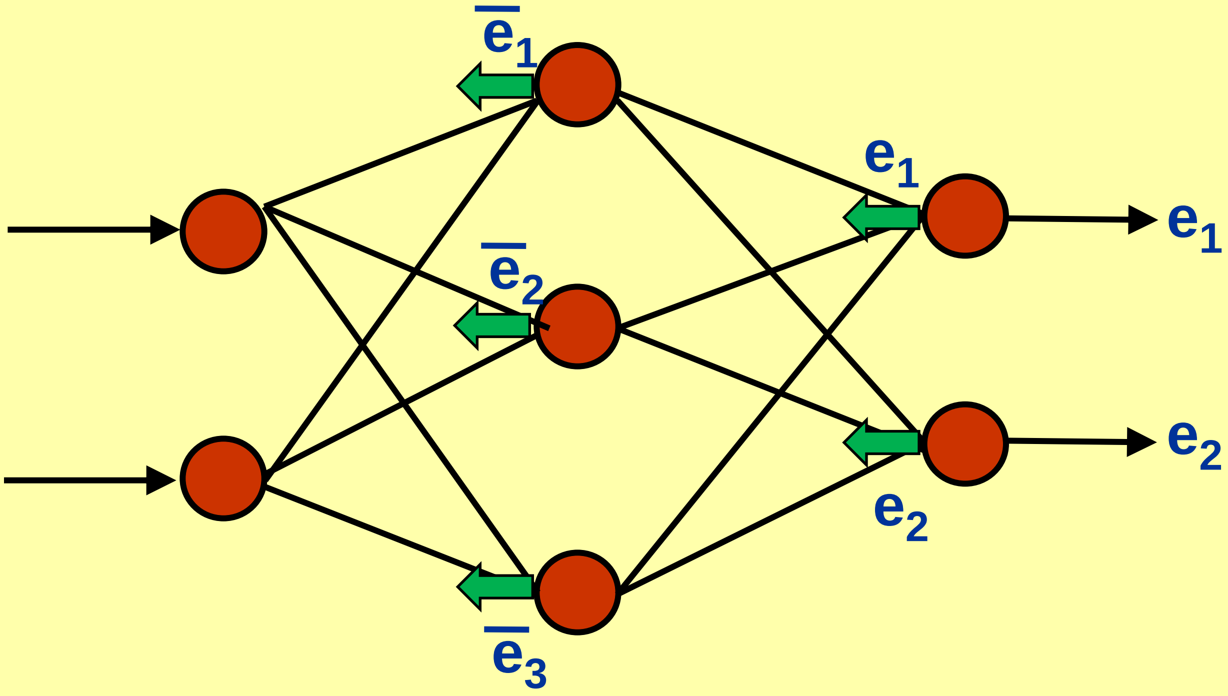
Error Back Propagation

Data

x_1	x_2	$\bar{y}_1$	$\bar{y}_2$
*	*	*	*
*	*	*	*
*	*	*	*



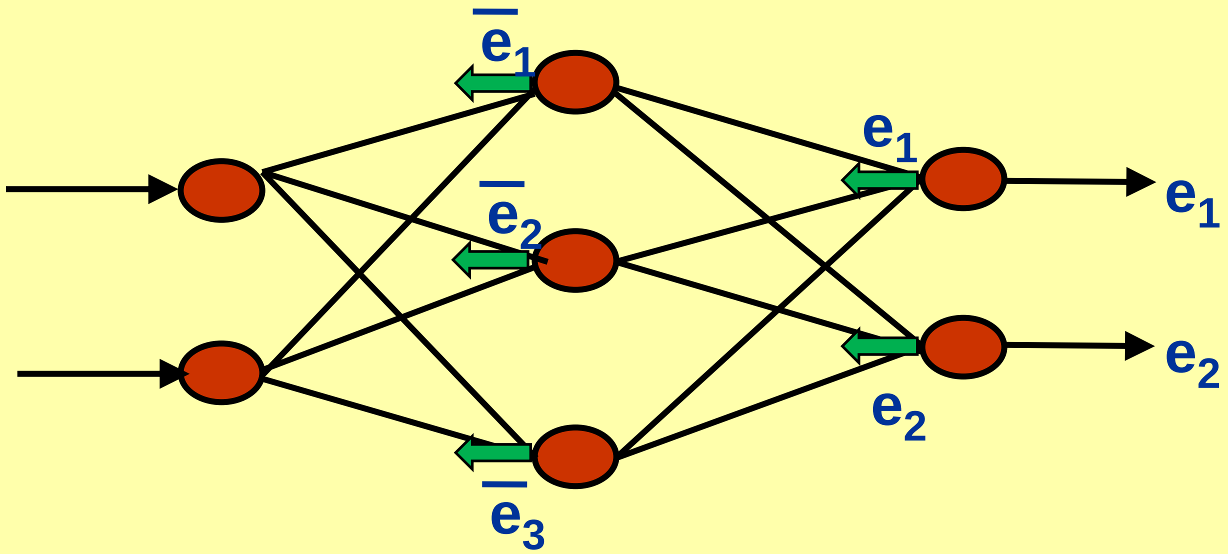
Error Back Propagation



$$e_1 = (y_1 - \bar{y}_1)$$
$$e_2 = (y_2 - \bar{y}_2)$$

$$\bar{e}_1 = (w_{11}e_1 + w_{12}e_2)\, f'(m_1)$$
$$\bar{e}_2 = (w_{21}e_1 + w_{22}e_2)\, f'(m_2)$$
$$\bar{e}_3 = (w_{31}e_1 + w_{32}e_2)\, f'(m_3)$$

Error Back Propagation

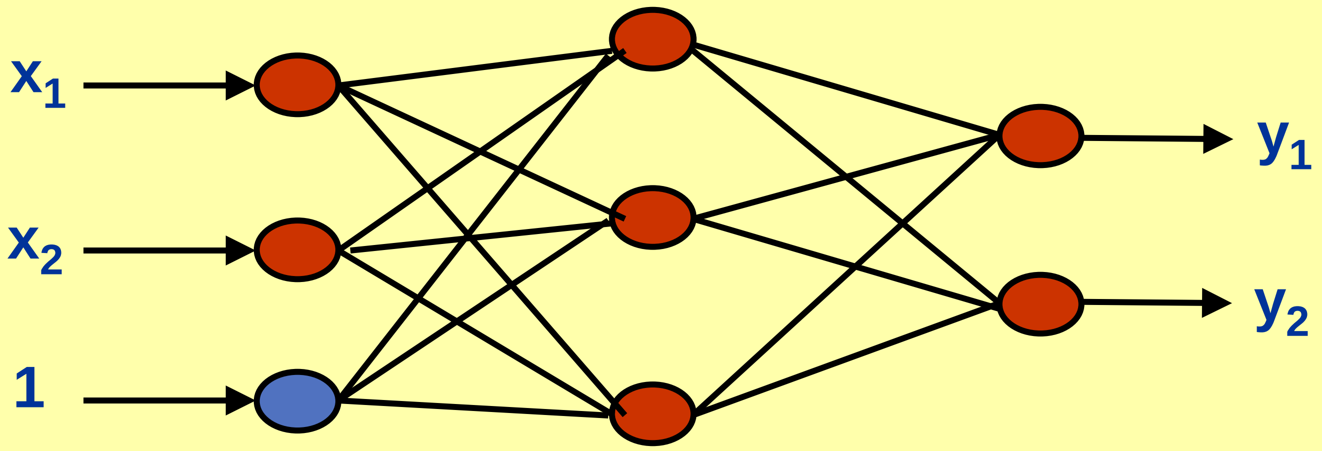


Computing Derivatives:

(back propagated error) (output of previous neuron)

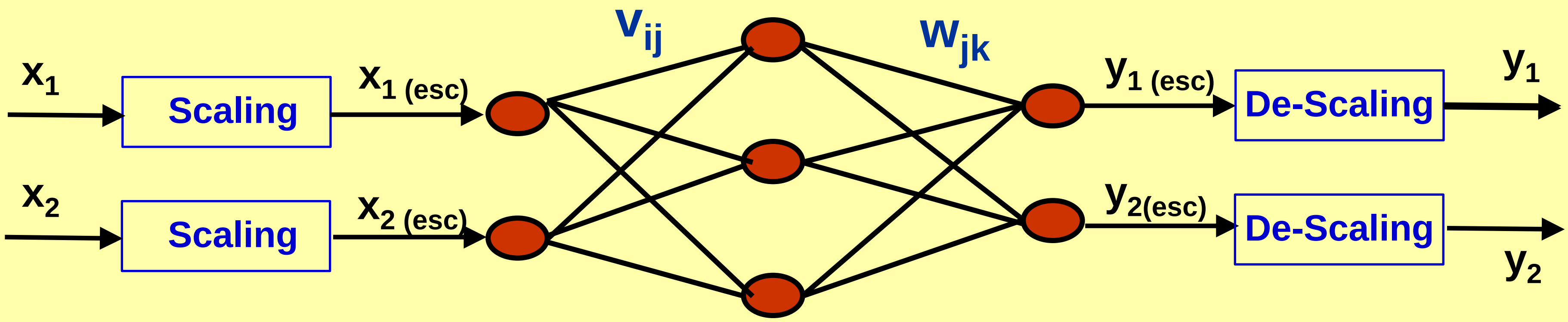
$$\frac{\partial J}{\partial v_{ij}} = e_j\, x_i \qquad\qquad \frac{\partial J}{\partial w_{jk}} = e_k\, n_j$$

Bias Neuron



In some cases, learning significantly improves with an additional input neuron having a constant input. This is the bias neuron.

Input – Output Scaling



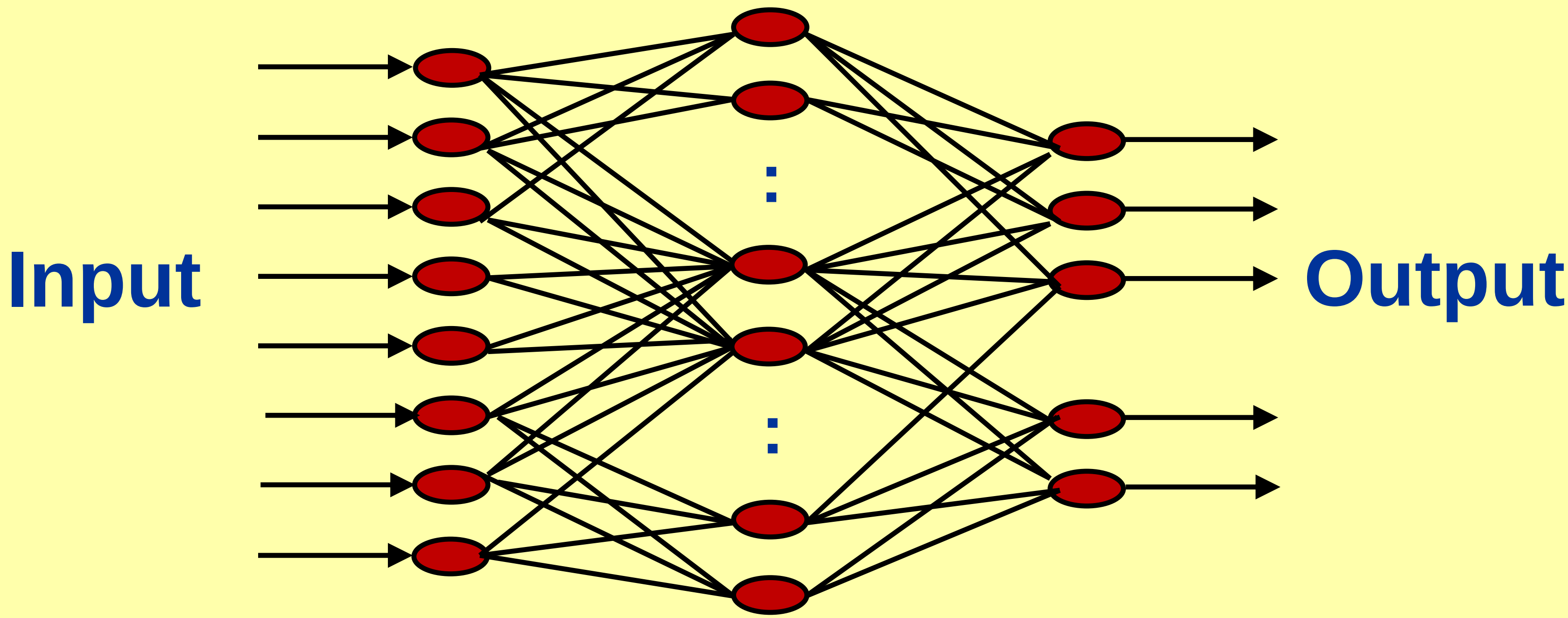
Given the saturation characteristics of neuron activation functions (sigmoid, gaussian) is desirable that the inputs to the neuron do not be of large value. To achieve that:

- Inputs (and corresponding outputs) should be scaled to the range [-2 2] (for instance). Linear scaling.
- Weigths v_{ij} and w_{jk} should be of small value.

Face Recognition

Neural network for recognizing 10 faces

Neural Network for Face Recognition



Input: Face

Output: Code for each face

Face Recognition

Assigning a code to each face

Considering 10 faces, the code will be of 10 digits of 1's and 0's in an orthogonal scheme

Face 1:	1 0 0 0 0 0 0 0 0 0
Face 2:	0 1 0 0 0 0 0 0 0 0
Face 3:	0 0 1 0 0 0 0 0 0 0
Face 4:	0 0 0 1 0 0 0 0 0 0
:	: :
Face 9:	0 0 0 0 0 0 0 0 1 0
Face 10:	0 0 0 0 0 0 0 0 0 1

Face Recognition

Neural Network Inputs

Given that an image contains great amount of information, it should be reduced to be processed by the neural network.

There are several ways to accomplish this reduction:

- Principal Components Analysis PCA.
- Discrete Cosine Transformation Coefficients.
- Pixeling (used in this report)

Full Color
2808 x 2425

Face Recognition

Reducing the size of images - Pixeling

Full Color
2808 x 2425

Gray Scale
1826 x 1529
The face occupies the most of the image

Monocromatic
40 x 30
1200 pixels

Face Recognition

Network Input

Matrix 40x30

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 0
: : : : :
: : : : :
0 0 0 0 1 0 1 1 1 1 1 1 1 0 0 1 0 0 0 0
0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

The matrix should be transformed into vector

Face Recognition

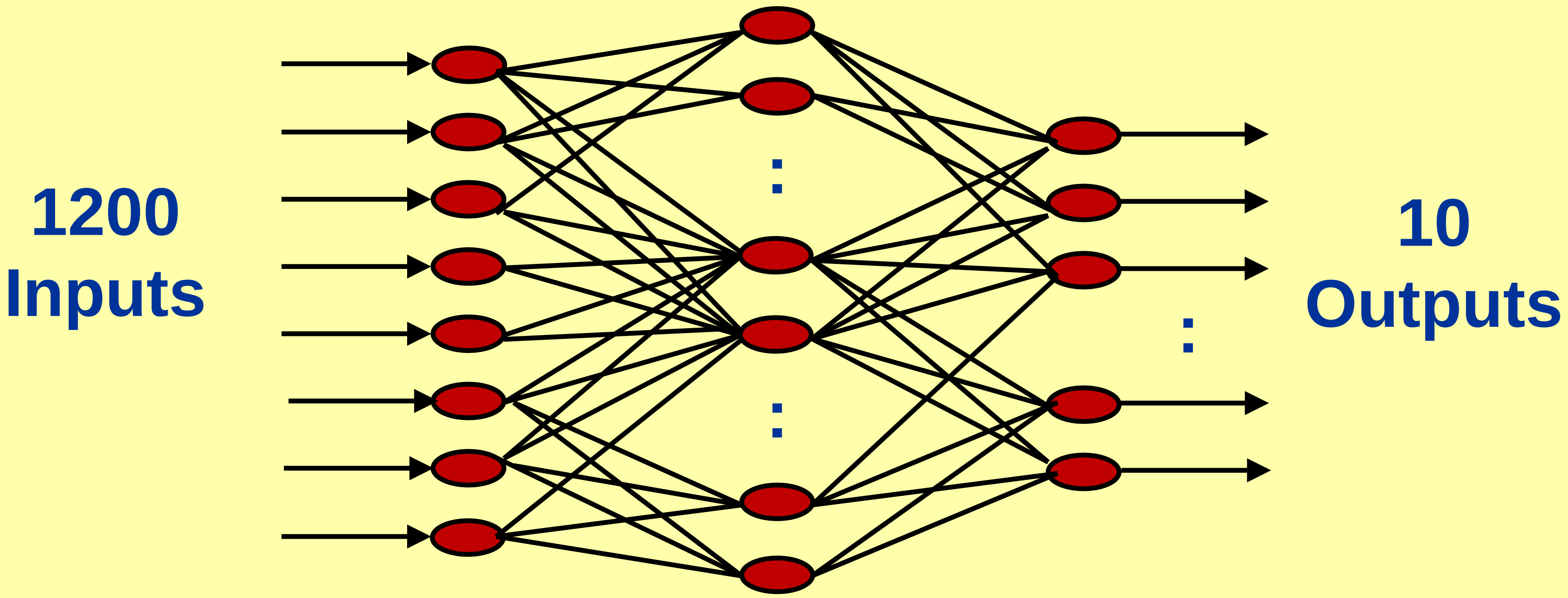
Network Input: Converting 40x30 matrix into 1200x1 vector

$$
\begin{vmatrix}
0&0&0&0&0&0&0&0&0&1&1&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&1&1&1&1&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&1&1&1&1&1&1&1&0&0&0&0&0&0&0\\
\vdots&&&&\vdots&&&&&\vdots&&&&\vdots&&&&\vdots&&\\
0&0&0&0&1&0&1&1&1&1&1&1&1&0&0&1&0&0&0&0\\
0&0&0&0&1&0&0&0&0&0&0&0&0&0&1&1&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0
\end{vmatrix}
\qquad
\begin{vmatrix}
0\\0\\0\\0\\\vdots\\1\\0\\1\\0\\\vdots\\1\\0\\0\\0
\end{vmatrix}
$$

40x30

1200x1

Neural Network for Face Recognition



To generate input-output training data, several faces of a person could be considered but all of them with the same output code

Neural Network for Face Recognition

Image Preprocessing - Pixeling

1213x1013

40x30

2644x2106

40x30

2854x2370

40x30

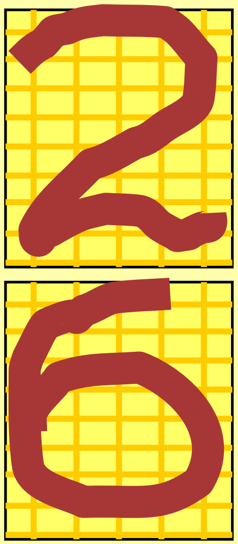
2446x2016

40x30

2507x2190

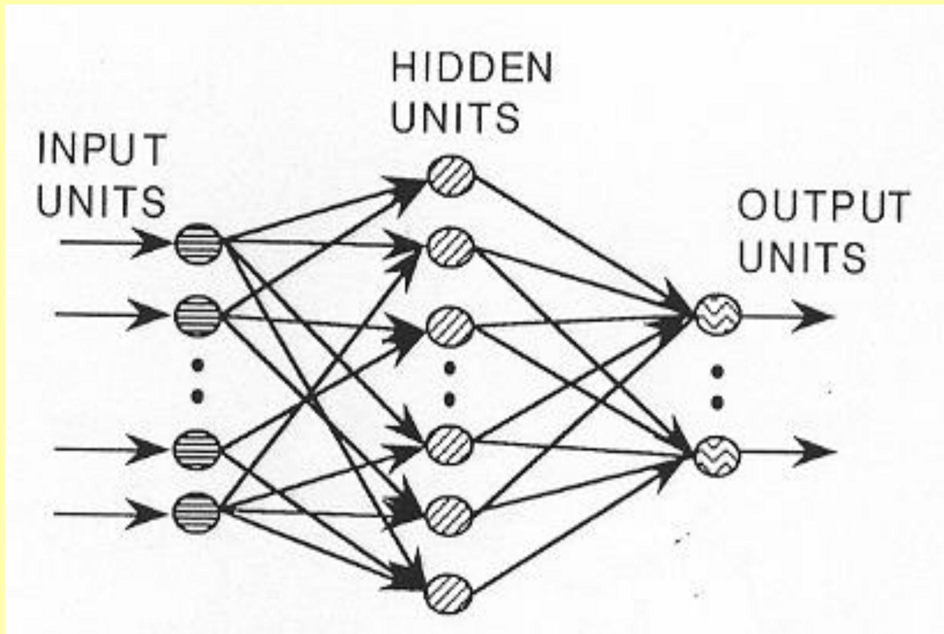
40x30

Number Recognition



$9 \times 6 = 54$

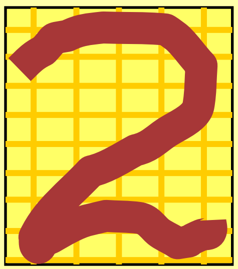
Inputs

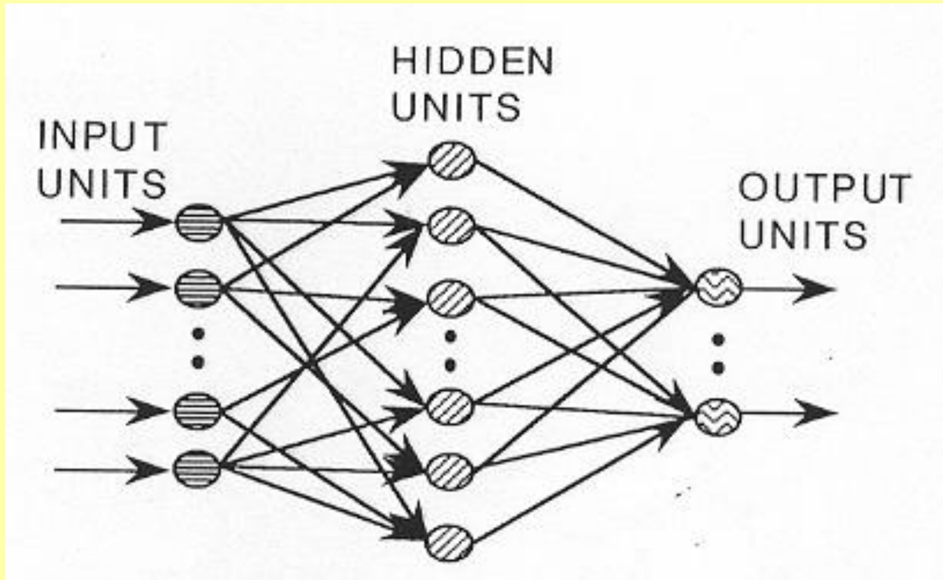


1	0	0		0
0	1	0		0
0	0	1		0
0	0	0		0
0	0	0	…	0
0	0	0		0
0	0	0		0
0	0	0		0
0	0	0		0
0	0	0		1

10 Outputs

Number Recognition



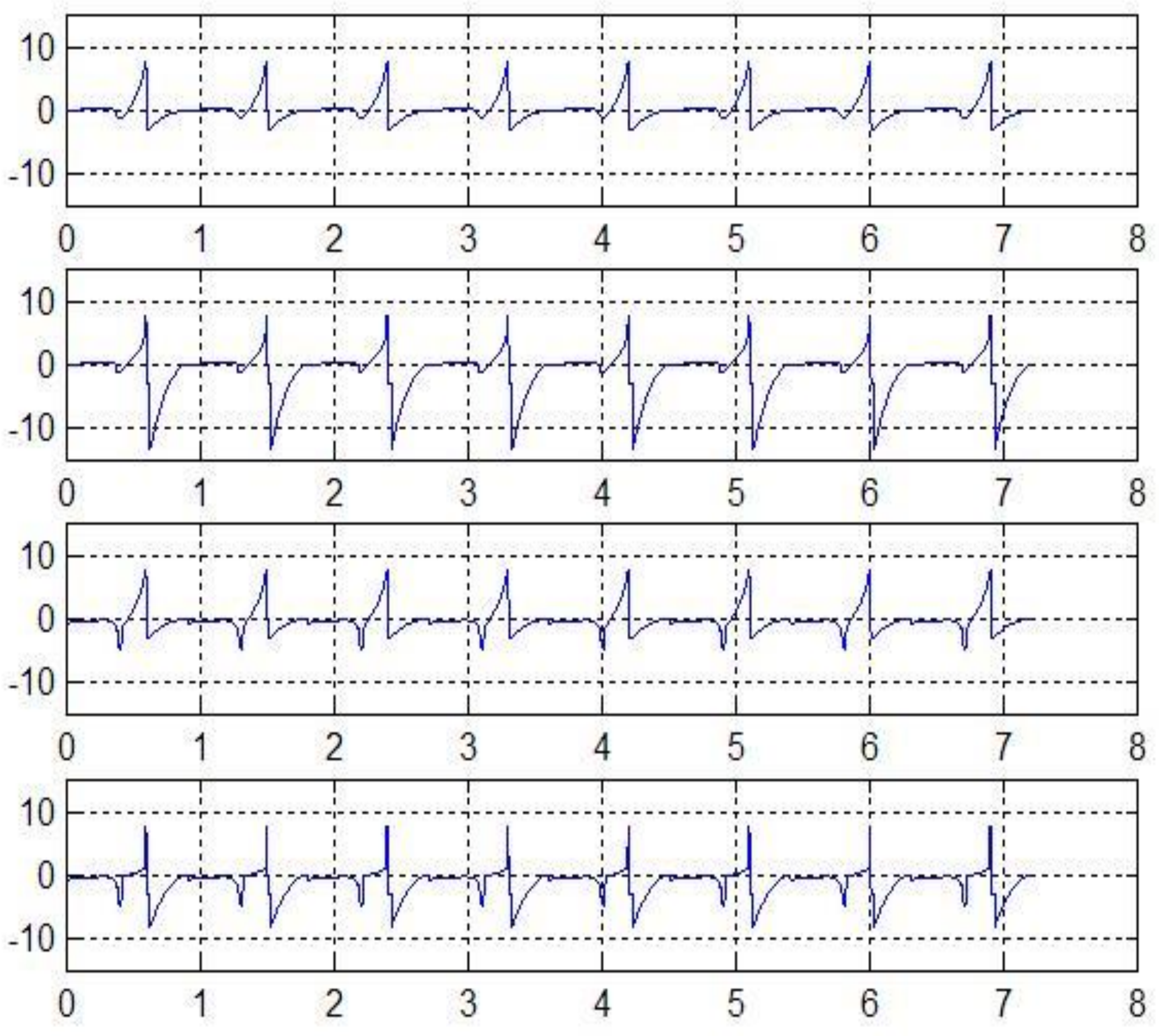


0
1
0
0
0
0
0
0
0
0

Recognition of 100% for training data

Recognition of 92% for validation data

Detection of Cardiac Anomalies



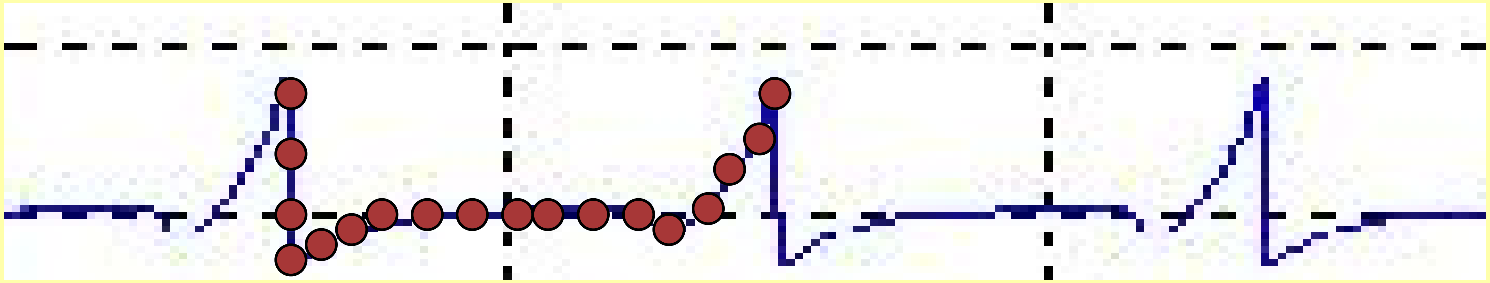
Normal

Anomaly 1

Anomaly 2

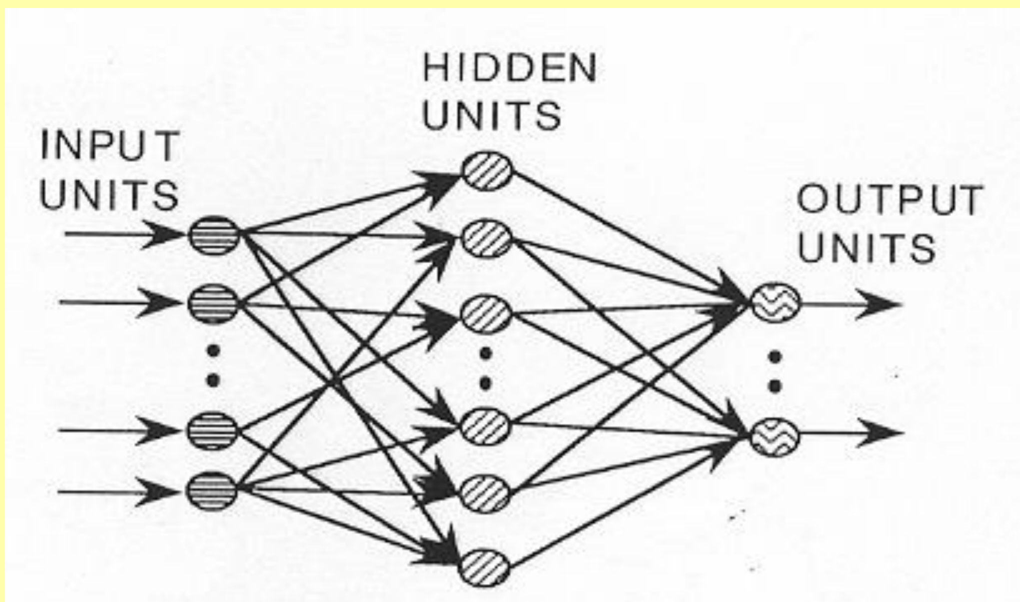
Anomaly 3

Training of Neural Network



600 samples in a period

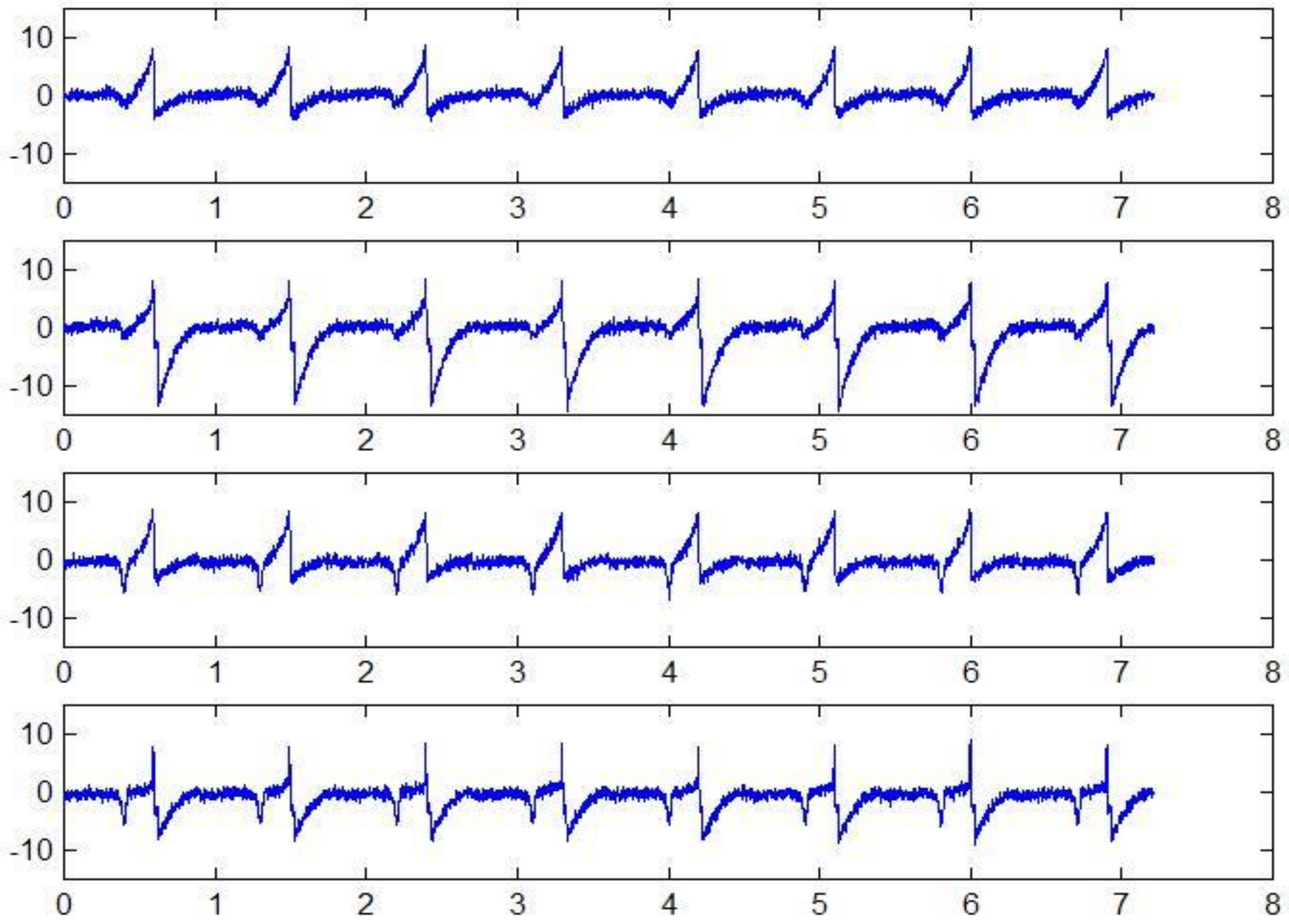
600 Inputs



1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

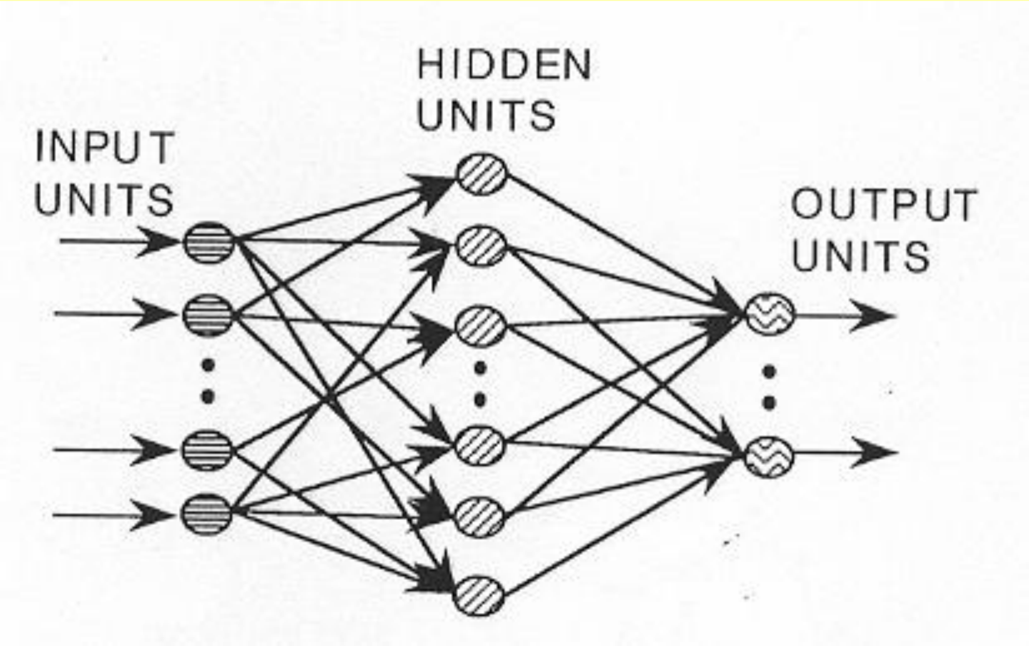
4 Outputs

Validation with Noisy Signals



Detection of Cardiac Anomalies

600 Inputs



4 Outputs

Recognition of 100% for low and medium level noise

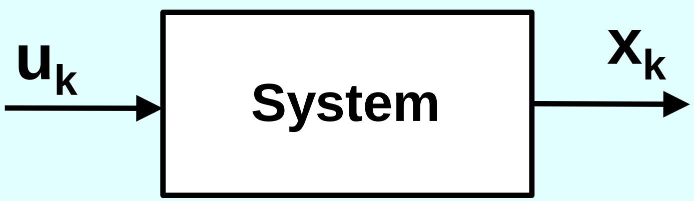
Recognition of 90% for high level noise

Dynamic Neural Networks

Modeling of Dynamical Systems

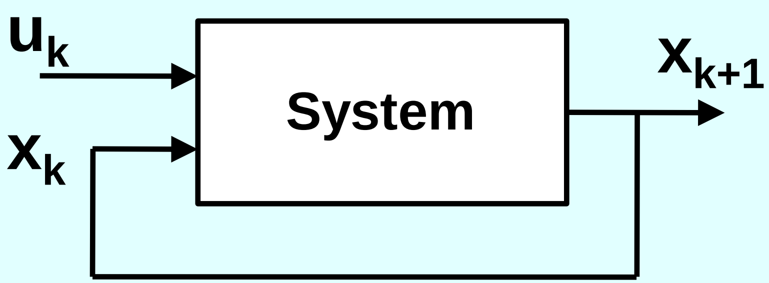
Modeling of Dynamical Systems

Static System



$$x_k = \Phi(u_k)$$

Dynamic System

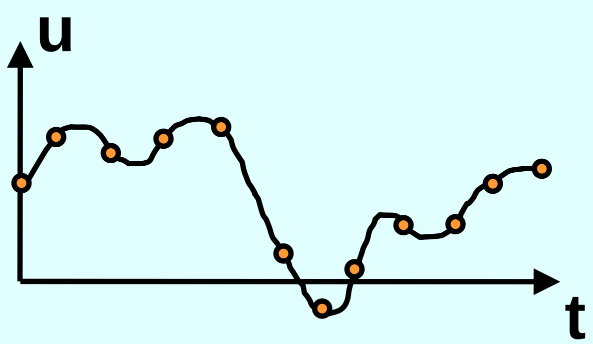


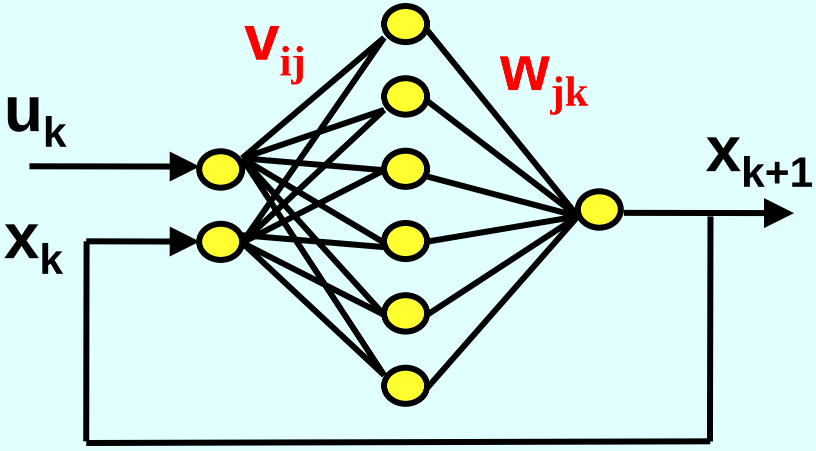
$$x_{k+1} = \Phi(x_k, u_k)$$

Output becomes input in the next step

Modeling of Dynamical Systems

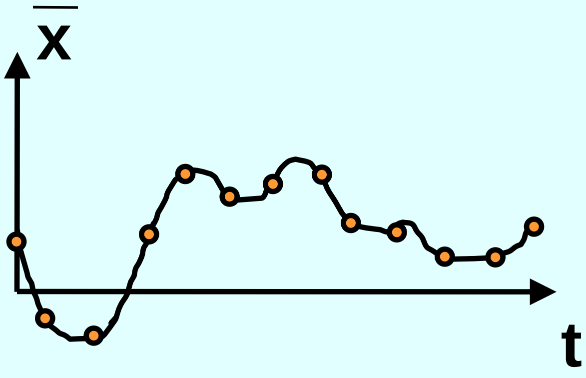
Input u





Desired Ouput $\bar{x}$

$$x_{k+1} = \Phi(x_k, u_k)$$



$x_0\ ,\ u_0 \longrightarrow x_1$

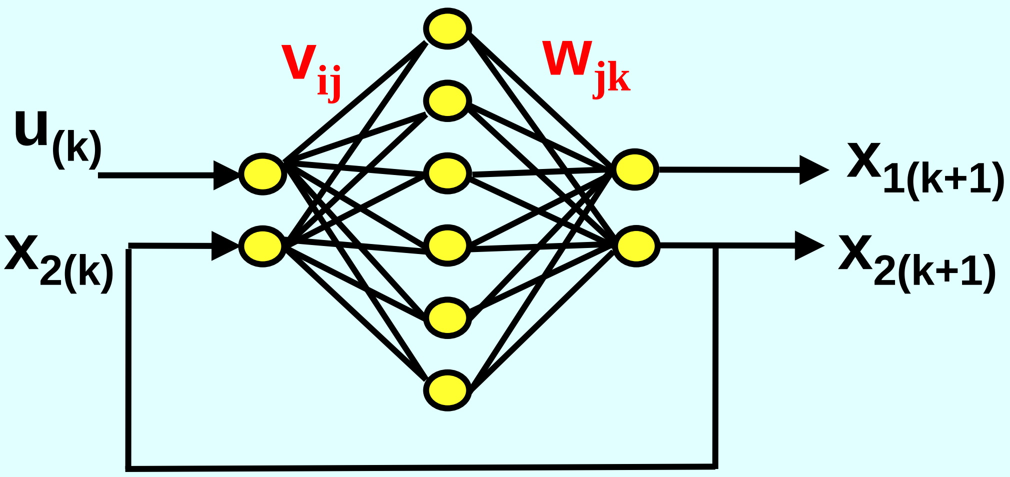
$x_1\ ,\ u_1 \longrightarrow x_2$

$x_2\ ,\ u_2 \longrightarrow x_3$

: :

$x_N\ ,\ u_N \longrightarrow x_N$

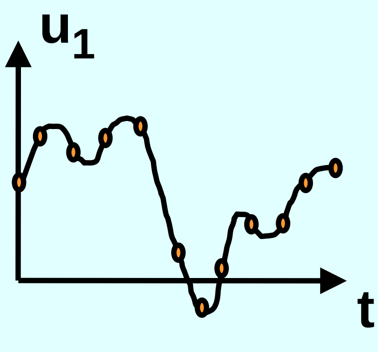
Modeling of Dynamical Systems

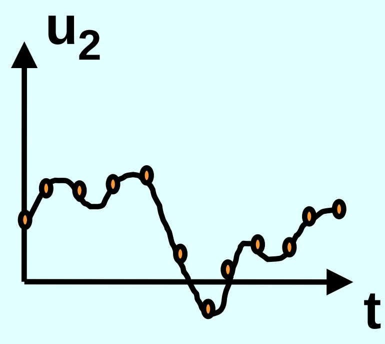


$$x_{k+1} = \Phi(x_k, u_k)$$

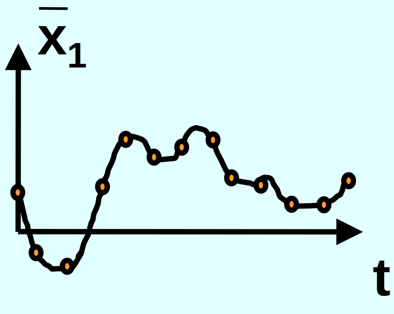
Modeling of Dynamical Systems

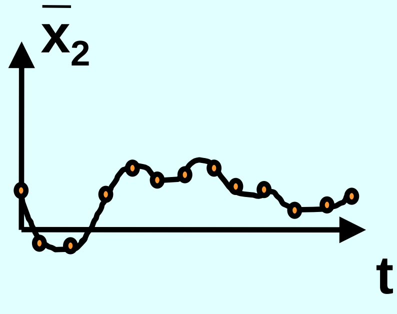
Input $u = \begin{vmatrix} u_1 \\ u_2 \end{vmatrix}$

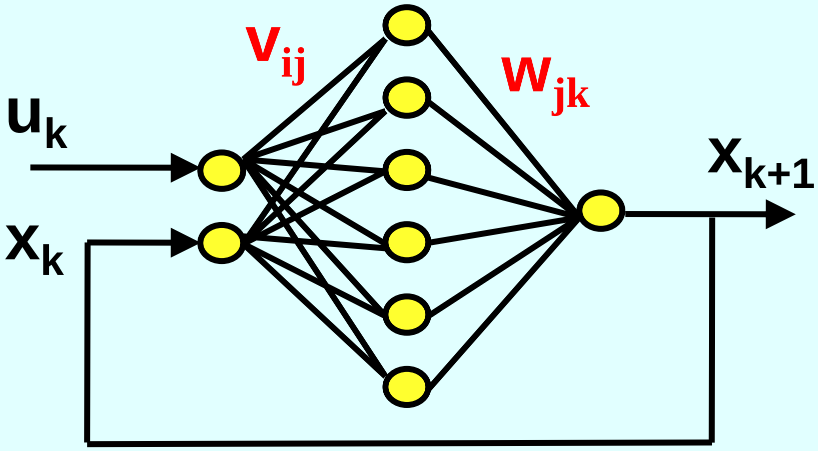




Desired Ouput $\overline{x} = \begin{vmatrix} \overline{x}_1 \\ \overline{x}_2 \end{vmatrix}$

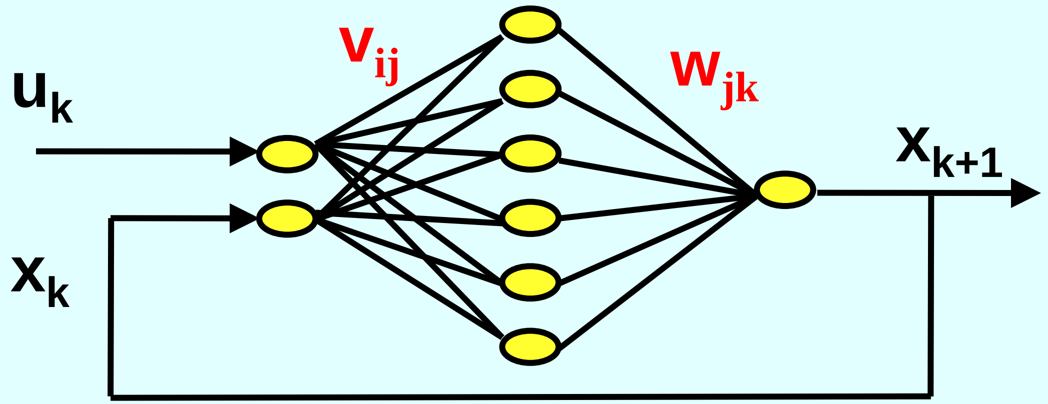






$$x_{k+1} = \Phi(x_k, u_k)$$

Training of Dynamical Neural Networks



Cost Function to be Minimized

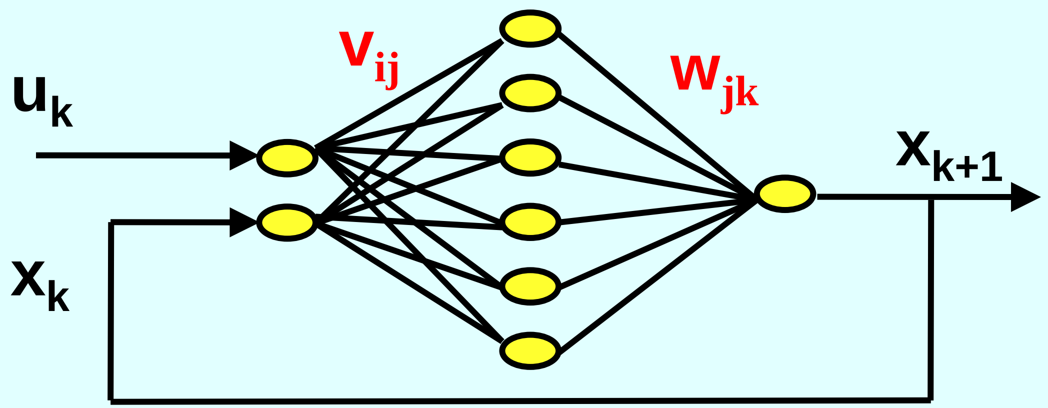
$$J = 0.5\,(x_1-\bar{x}_1)^2 + 0.5\,(x_2-\bar{x}_2)^2 + \cdots + 0.5\,(x_N-\bar{x}_N)^2$$

$$J = 0.5 \sum_{k=1}^{k=N} (x_k - \bar{x}_k)^2$$

$x_k \rightarrow$ Estado (Salida) de la red

$\bar{x}_k \rightarrow$ Salida deseada (data)

Training of Dynamical Neural Networks

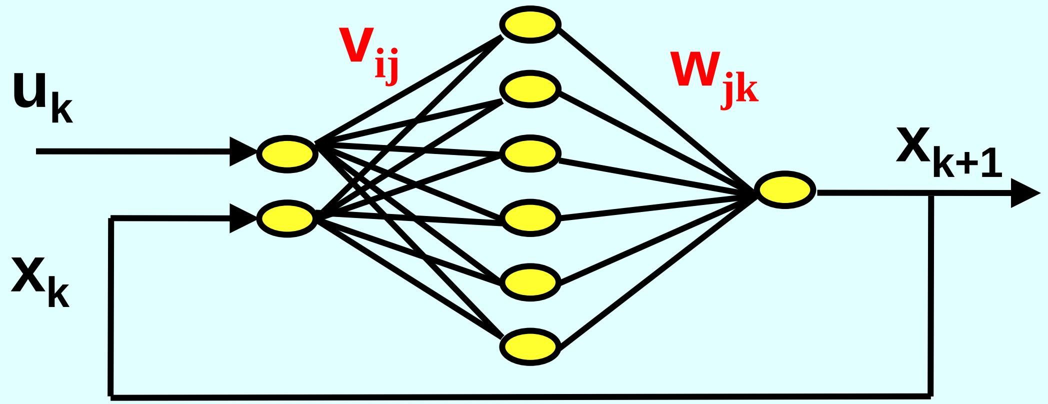


If x is a vector $\quad x = \begin{vmatrix} x_1 \\ x_2 \end{vmatrix}$

Cost Function to be Minimized

$$J = 0.5 \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T (x_k - \overline{x}_k)$$

Training of Dynamical Neural Networks



Cost Function to be Minimized

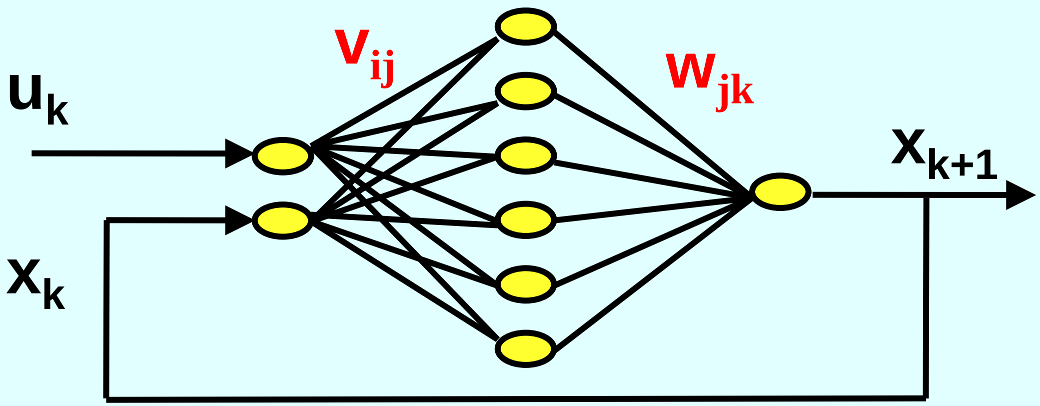
$$J = 0.5\,(x_1-\bar{x}_1)^2 + 0.5\,(x_2-\bar{x}_2)^2 + \cdots\cdots + 0.5\,(x_N-\bar{x}_N)^2$$

$$v_{ij} = v_{ij} - \eta\,\frac{\overline{\partial J}}{\overline{\partial v_{ij}}}$$

$$w_{jk} = w_{jk} - \eta\,\frac{\overline{\partial J}}{\overline{\partial w_{jk}}}$$

Total partial derivatives

Training of Dynamical Neural Networks



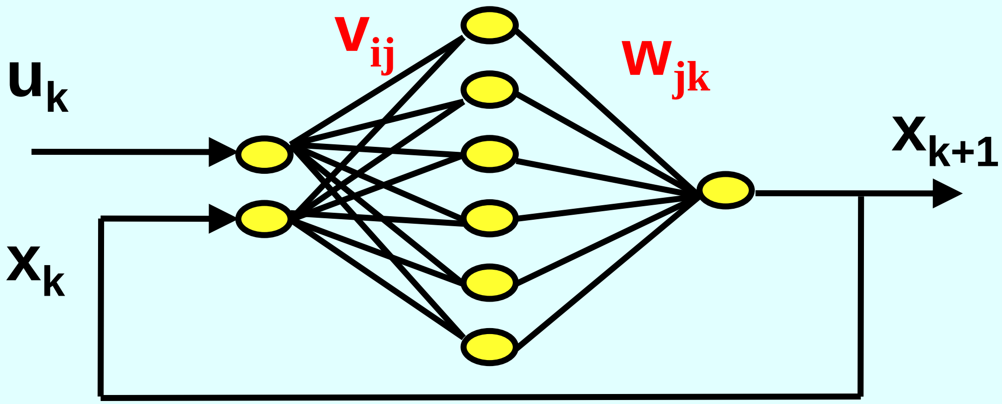
Cost Function to be Minimized $J = 0.5 \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T (x_k - x_k)$

$$\frac{\overline{\partial J}}{\overline{\partial v}} = \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T \frac{\overline{\partial x_k}}{\overline{\partial v}}$$

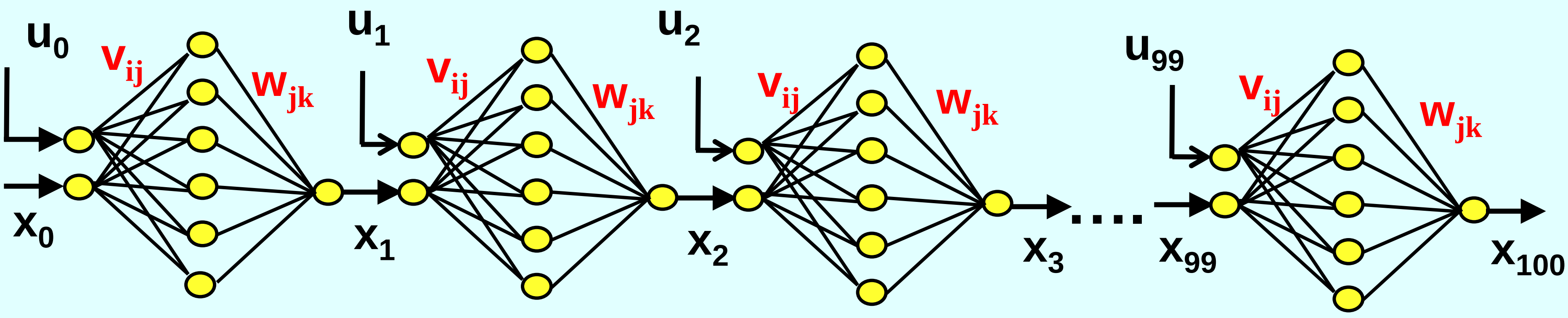
$$\frac{\overline{\partial J}}{\overline{\partial w}} = \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T \frac{\overline{\partial x_k}}{\overline{\partial w}}$$

Total partial derivative of x_k

Training of Dynamic Neural Networks



Unfolding the Network Along Time



Training of Dynamical Neural Networks

$$v_{ij} = v_{ij} - \eta \frac{\overline{\partial J}}{\overline{\partial v_{ij}}}$$

$$w_{jk} = w_{jk} - \eta \frac{\overline{\partial J}}{\overline{\partial w_{jk}}}$$

Total partial derivatives

$z = 3y + 2x$

$y = 4x + 5r$

$r = 2x + 6s$

Simple Derivative

$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial x} = 2$$

Total Derivative

$$\frac{\overline{\partial z}}{\overline{\partial x}} = \frac{\partial z}{\partial x} + \frac{\partial z}{\partial y}\frac{\partial y}{\partial x} + \frac{\partial z}{\partial y}\frac{\partial y}{\partial r}\frac{\partial r}{\partial x}$$

Training of Dynamical Neural Networks

Computation of Total Partial Derivatives

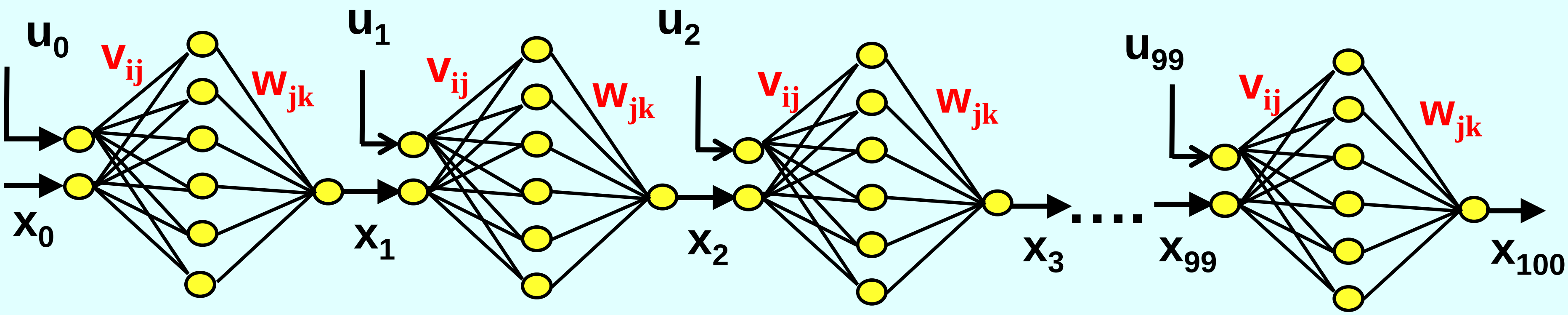
- **Back Propagation Through Time BPTT**

  Paul Werbos, 1972

- **Dynamic Back Propagation DBP**

  Kumpati Narendra, 1989

Dynamic Back Propagation

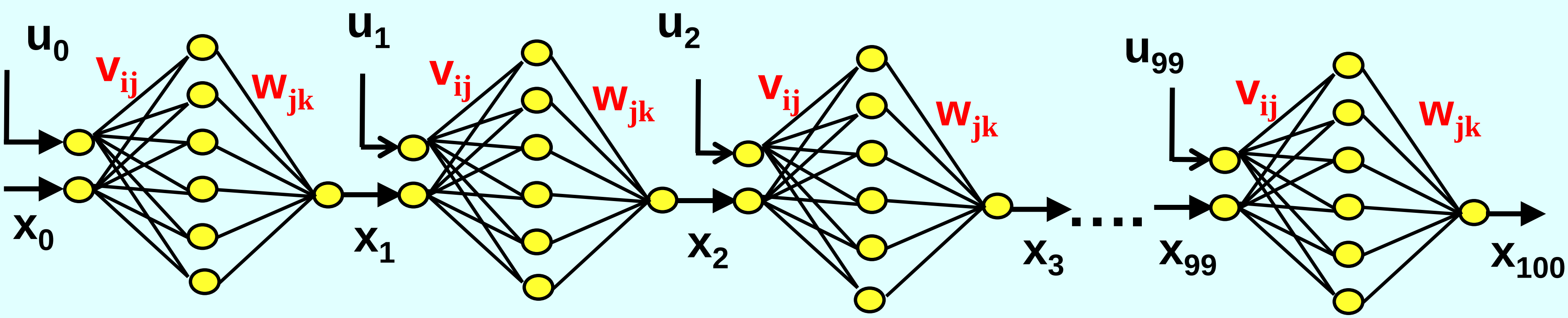


$$\frac{\overline{\partial x_1}}{\overline{\partial v}} = \frac{\partial x_1}{\partial v}$$

$$\frac{\overline{\partial x_2}}{\overline{\partial v}} = \frac{\partial x_2}{\partial v} + \frac{\partial x_2}{\partial x_1}\frac{\overline{\partial x_1}}{\overline{\partial v}}$$

$$\frac{\overline{\partial x_3}}{\overline{\partial v}} = \frac{\partial x_3}{\partial v} + \frac{\partial x_3}{\partial x_2}\frac{\overline{\partial x_2}}{\overline{\partial v}}$$

Dynamic Back Propagation



$$\frac{\overline{\partial x_{k+1}}}{\overline{\partial v}} = \frac{\partial x_{k+1}}{\partial v} + \frac{\partial x_{k+1}}{\partial x_k}\,\frac{\overline{\partial x_k}}{\overline{\partial v}}$$

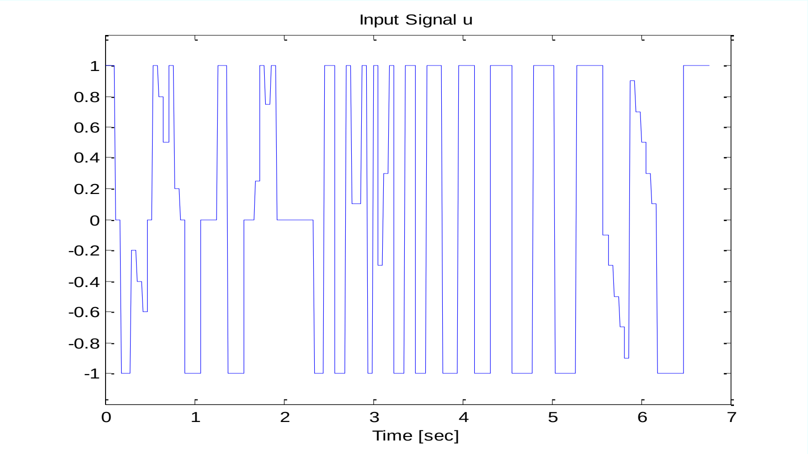
Recursive expression for computation of total partial derivatives

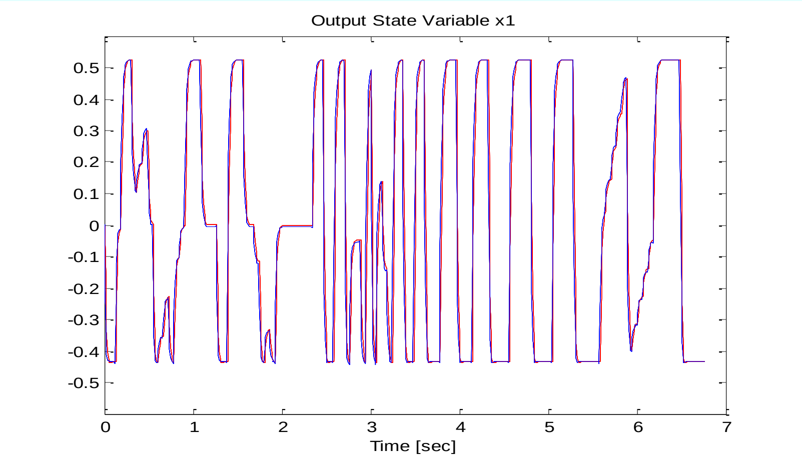
Modeling of Nonlinear Dynamic System

One Input and Two Outputs

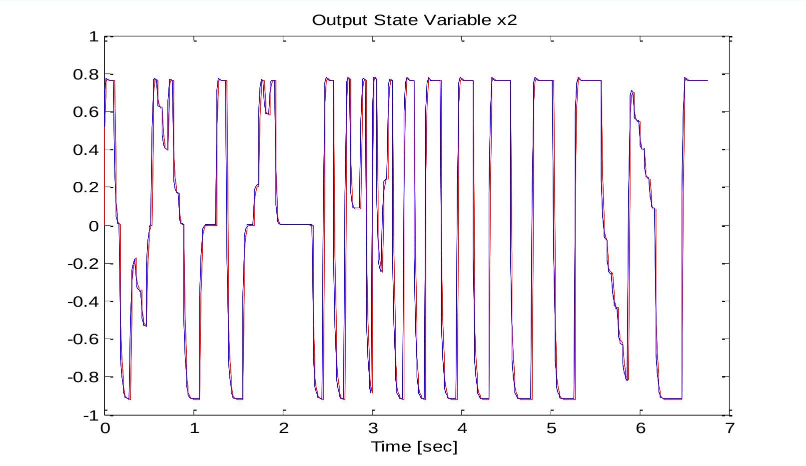
Network Training

Input Signal u





Output Signal x1



Output Signal x2

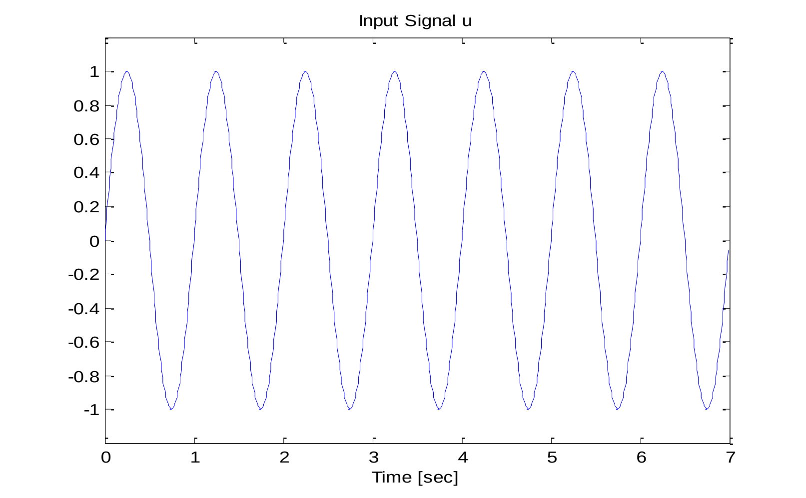
Training Signal

Model Output

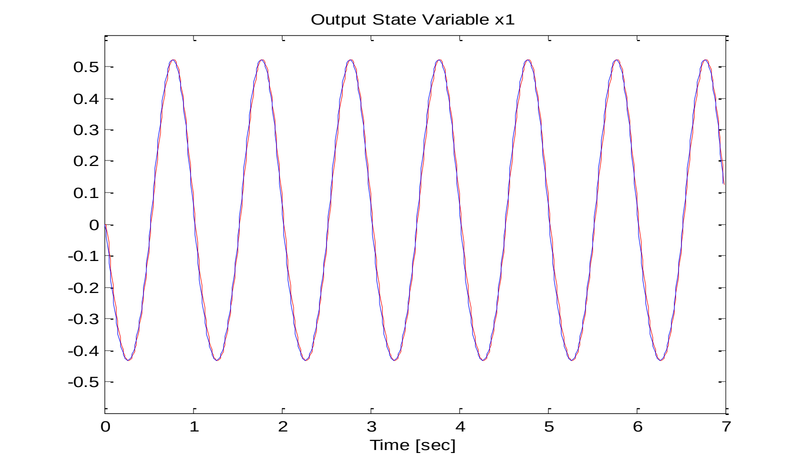
Modeling of Nonlinear Dynamic System

Validation: Input-Output Signals

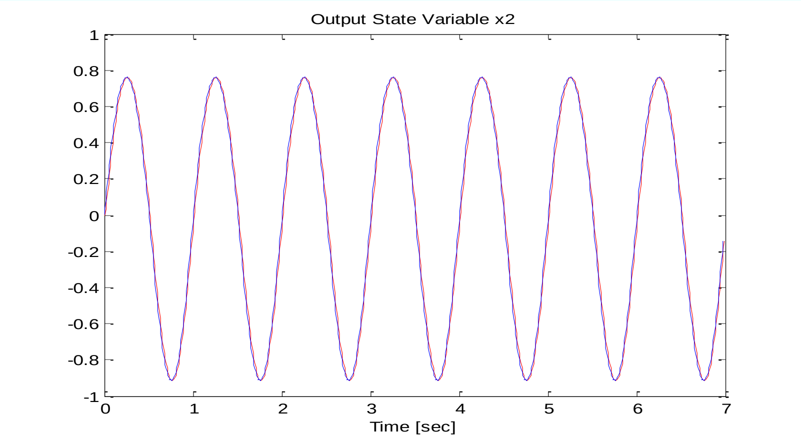
Input Signal u



Output Signal x1



Output Signal x2



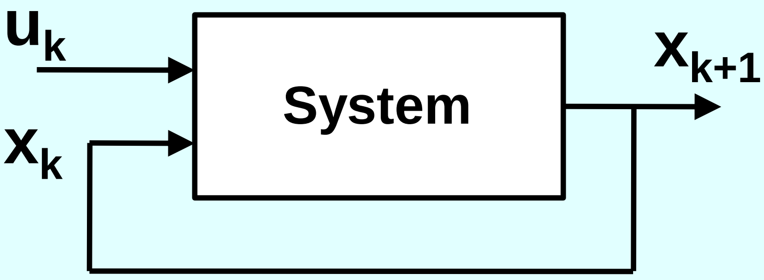
Training Signal

Model Output

Modeling of Nonlinear Dynamic System

Matlab Simulation

Dynamical system with 1 input and 3 outputs



$$x = \begin{vmatrix} x_1 \\ x_2 \\ x_3 \end{vmatrix}$$

Nonlinear system

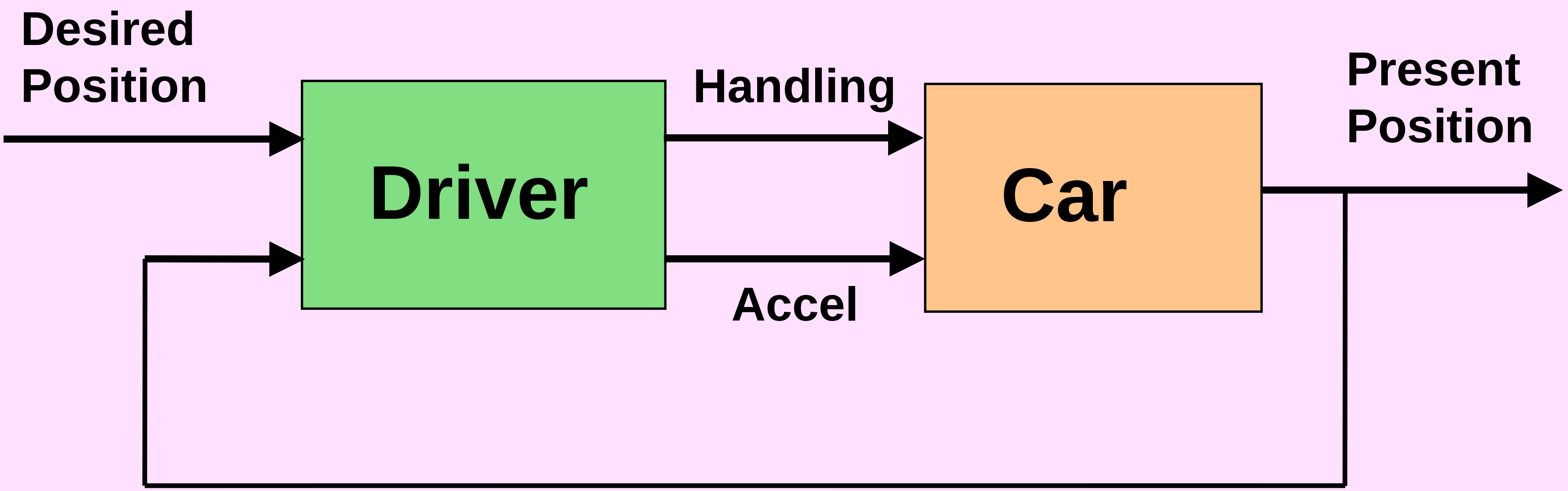
$$x_k = Ax_k + Bu_k + Gx_k u_k$$

Dynamic Neural Networks

Control of Dynamical Systems

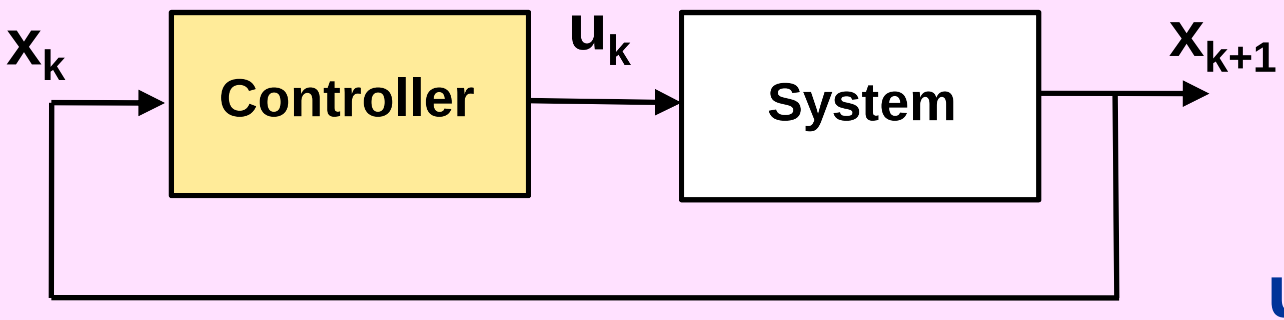
Car Driving

A Control Problem



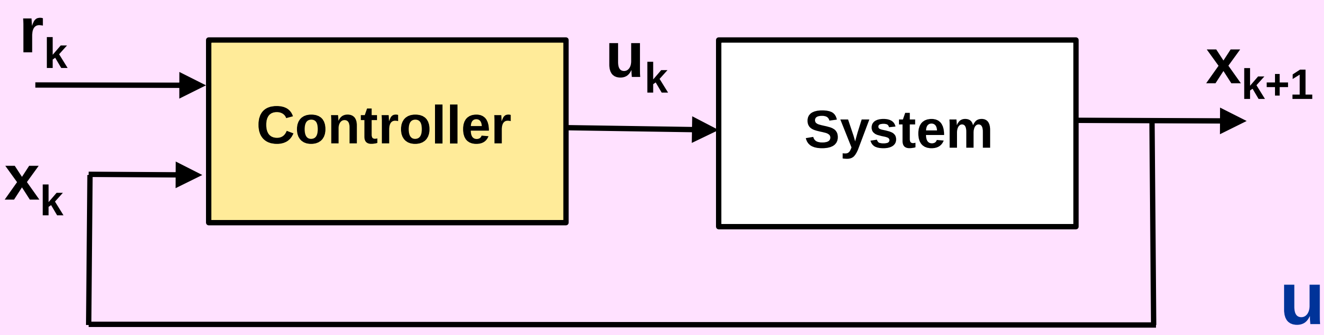
Control of Dynamical Sytems

Stabilization



$$u_k = \Omega(x_k)$$

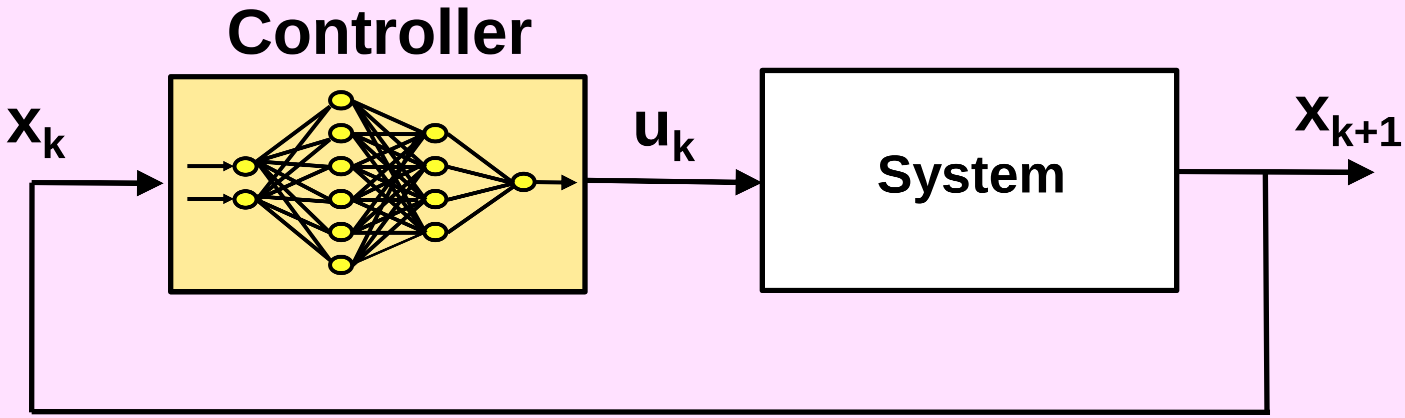
Tracking



$$u_k = \Omega(x_{k,}\ r_k)$$

Control of Dynamical Sytems

Stabilization



Controller

$$u_k = \Omega(x_k)$$

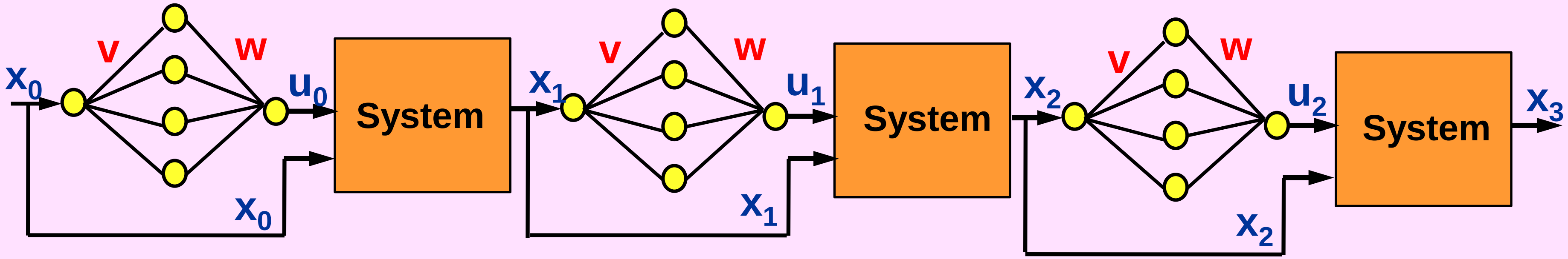
System

$$x_{k+1} = \Phi(x_k, u_k)$$

Represented by:

- **Neural Network**
- **State Equation**

Training of Neuro-Controller



Cost Function to be Minimized

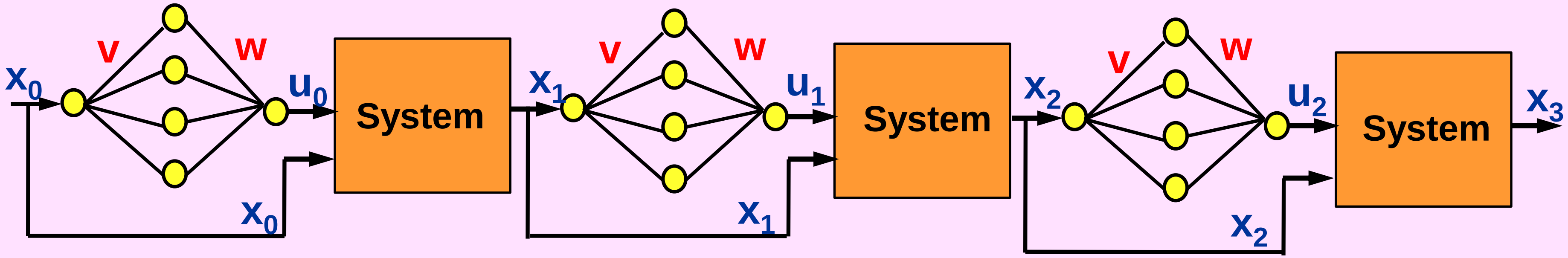
$$J = 0.5\,(x_1-\bar{x}_1)^2 + 0.5\,(x_2-\bar{x}_2)^2 + \cdots\cdots + 0.5\,(x_N-\bar{x}_N)^2$$

$$J = 0.5 \sum_{k=1}^{k=N} (x_k - \bar{x}_k)^2$$

$x_k \rightarrow$ **Estado (Salida)**

$\bar{x}_k \rightarrow$ **Salida deseada**

Training of Neuro-Controller



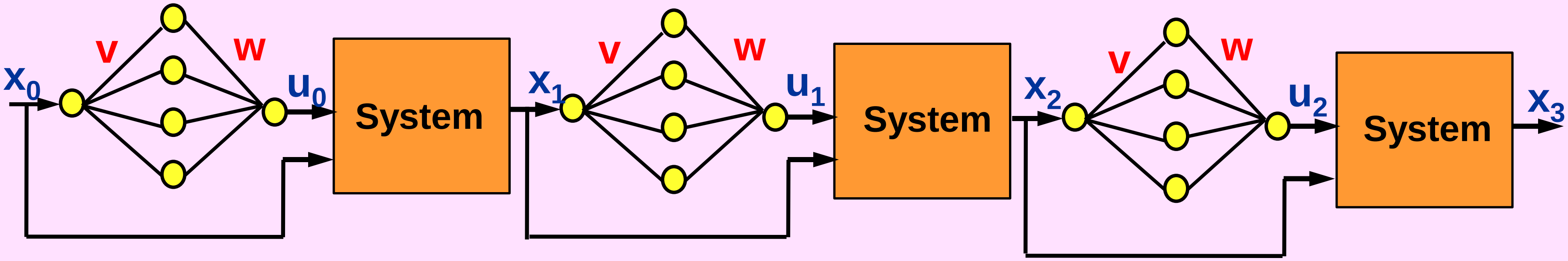
If x is a vector $\quad x = \begin{vmatrix} x_1 \\ x_2 \end{vmatrix}$

Cost Function to be Minimized

$$J = 0.5 \sum_{k=1}^{k=N} (x_k - \bar{x}_k)^T (x_k - \bar{x}_k)$$

$\bar{x}_k =$ **Desired output**

Training of Neuro-Controller



Cost Function to be Minimized

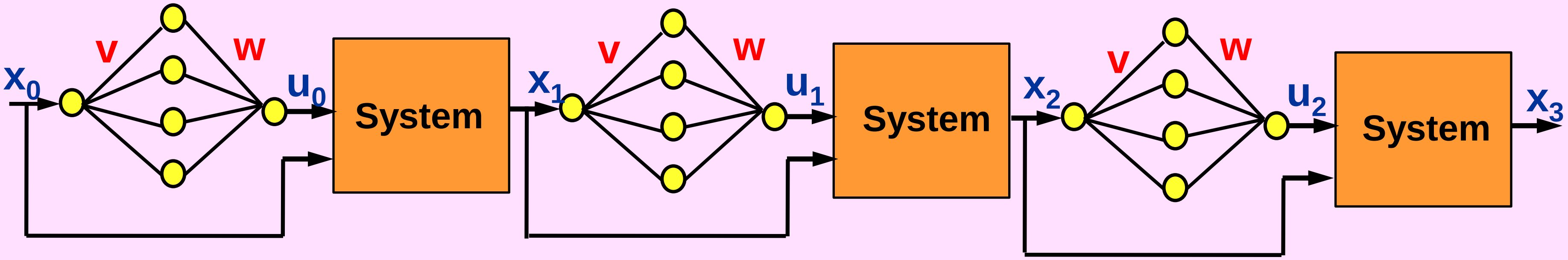
$$J = 0.5\,(x_1 - \bar{x}_1)^2 + 0.5\,(x_2 - \bar{x}_2)^2 + \cdots\cdots + 0.5\,(x_N - \bar{x}_N)^2$$

$$v_{ij} = v_{ij} - \eta \frac{\overline{\partial J}}{\overline{\partial v_{ij}}}$$

$$w_{jk} = w_{jk} - \eta \frac{\overline{\partial J}}{\overline{\partial w_{jk}}}$$

Total partial derivatives

Training of Neuro-Controller



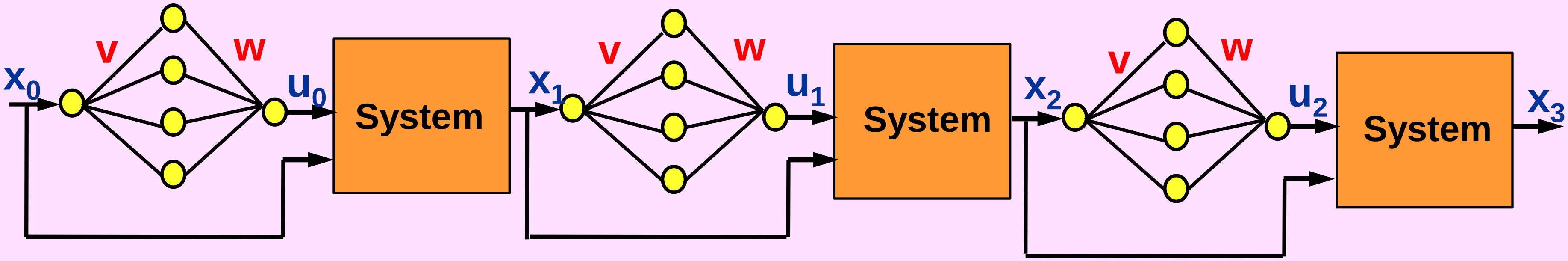
Cost Function to be Minimized $J = 0.5 \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T (x_k - x_k)$

$$\frac{\overline{\partial J}}{\overline{\partial v}} = \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T \frac{\overline{\partial x_k}}{\overline{\partial v}}$$

$$\frac{\overline{\partial J}}{\overline{\partial w}} = \sum_{k=1}^{k=N} (x_k - \overline{x}_k)^T \frac{\overline{\partial x_k}}{\overline{\partial w}}$$

Total partial derivative of x_k

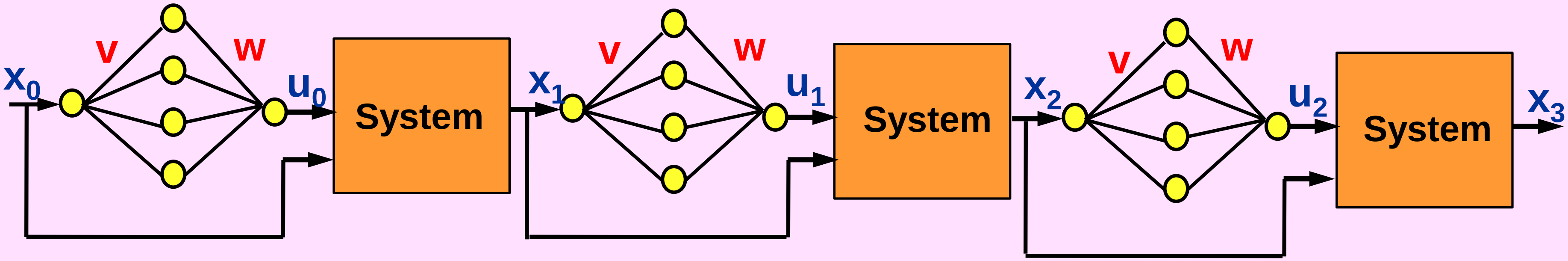
Dynamic Back Propagation



$$\frac{\overline{\partial x_{k+1}}}{\overline{\partial v}} = \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial v} + \left(\frac{\partial x_{k+1}}{\partial x_k} + \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial x_k}\right)\frac{\overline{\partial x_k}}{\overline{\partial v}}$$

Recursive expression for computation of total partial derivatives

Dynamic Back Propagation

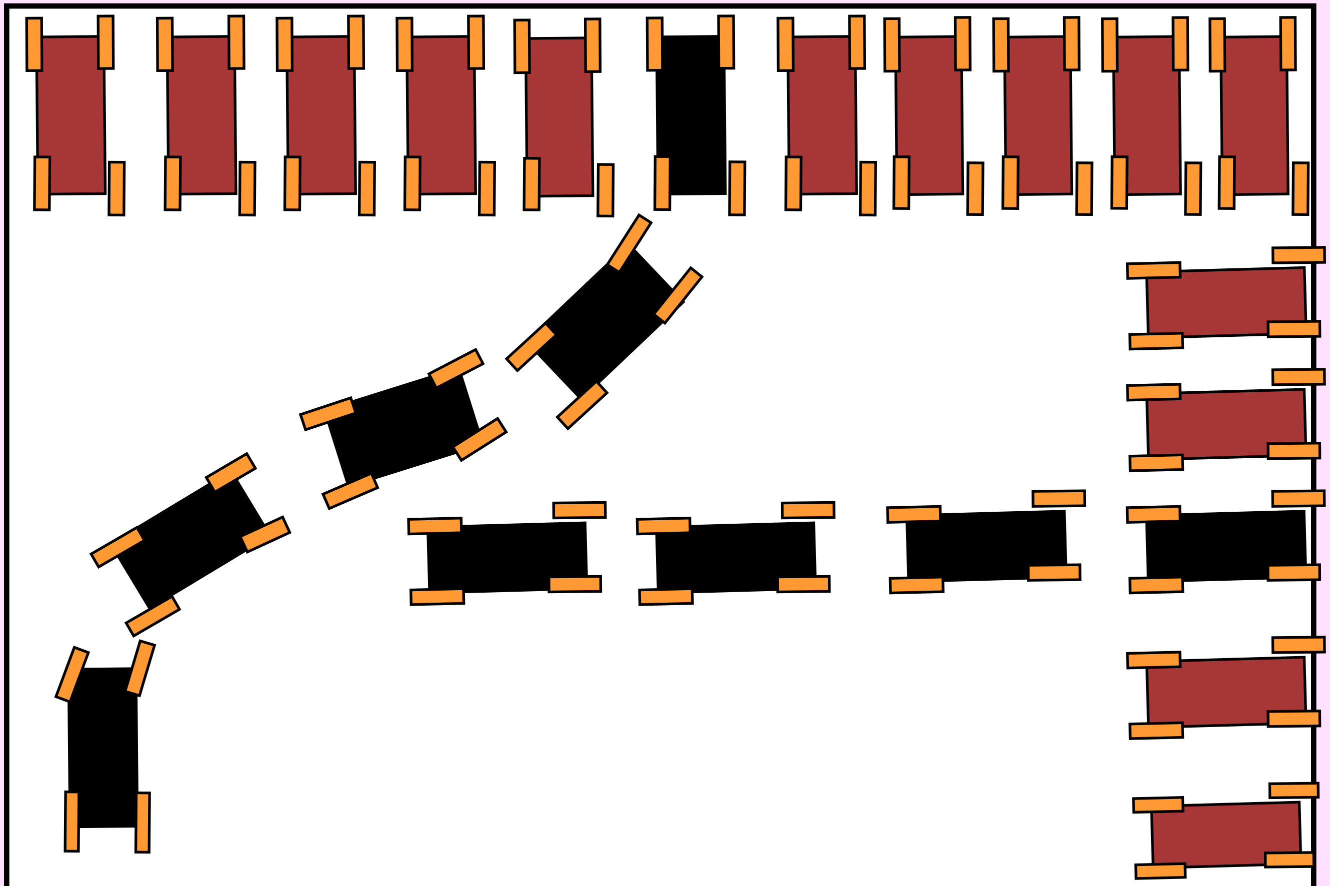


$$\frac{\overline{\partial x_{k+1}}}{\overline{\partial v}} = \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial v} + \left(\frac{\partial x_{k+1}}{\partial x_k} + \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial x_k}\right)\frac{\overline{\partial x_k}}{\overline{\partial v}}$$

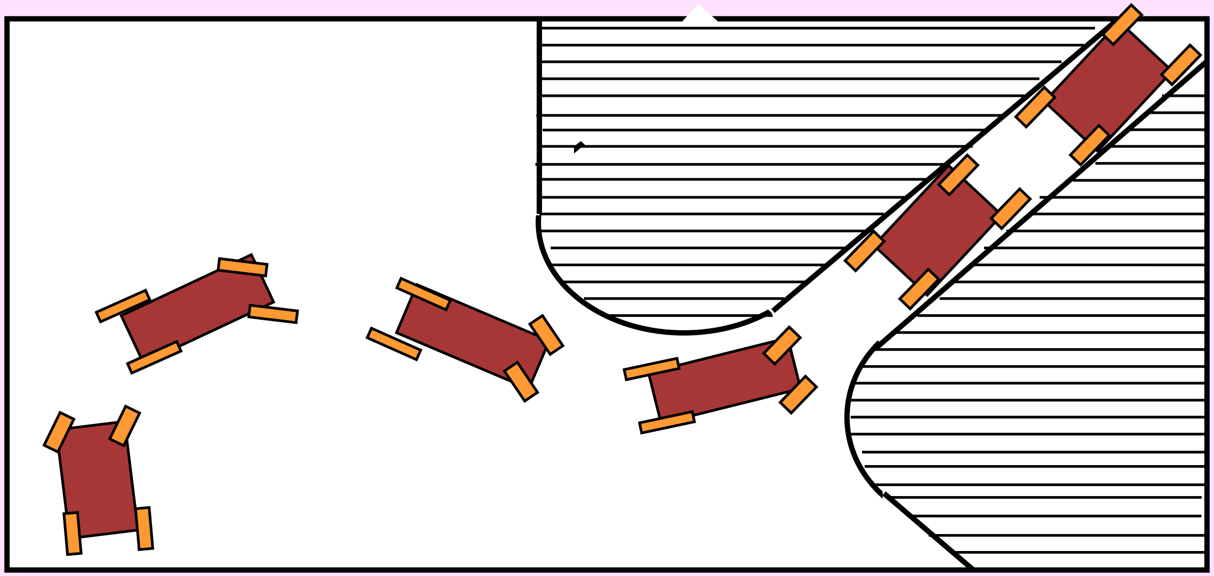
Computed with the system model

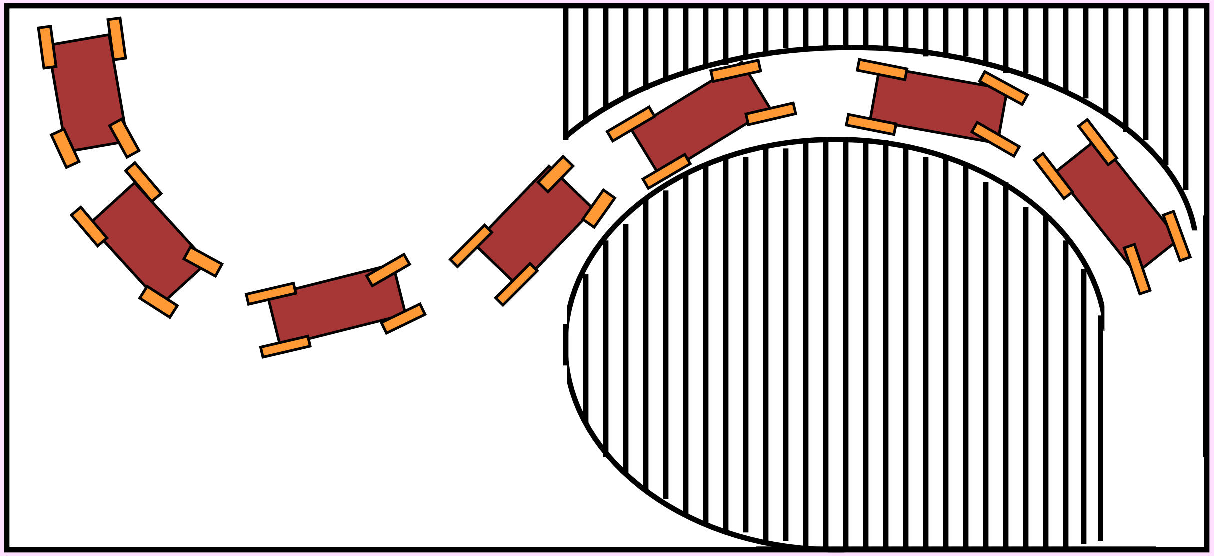
Computed with the neural controller

Positioning of Mobile Robots

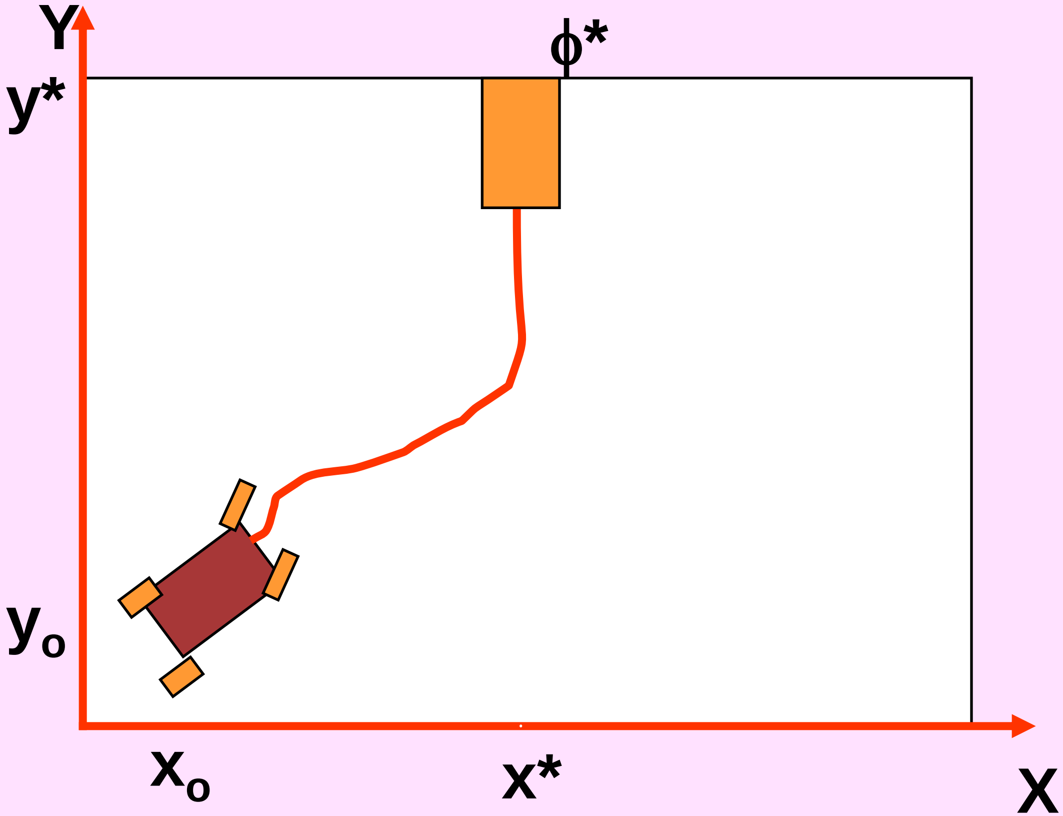


Mobile Robot Following a Road





Control Problem



How to compute steer angle δ

Initial Position

x_o

y_o

ϕ_o

δ

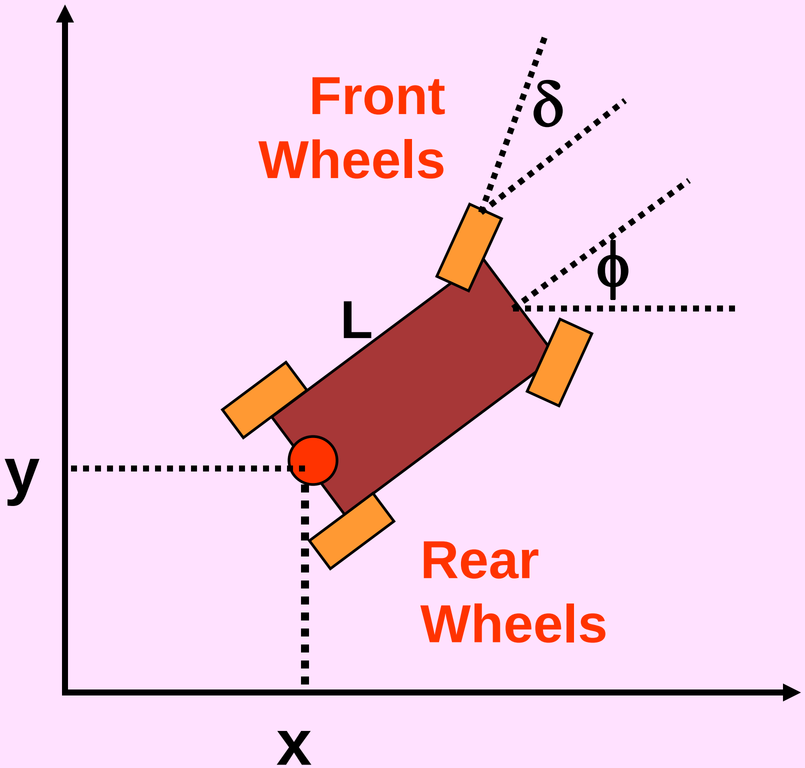
$x^* = 50$

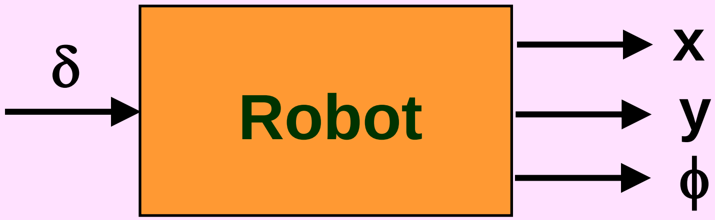
$y^* = 100$

$\phi^* = \pi/2$

Desired Position

Robot Model





$$x(k+1) = x(k) + v\Delta t \cos(\phi(k))$$

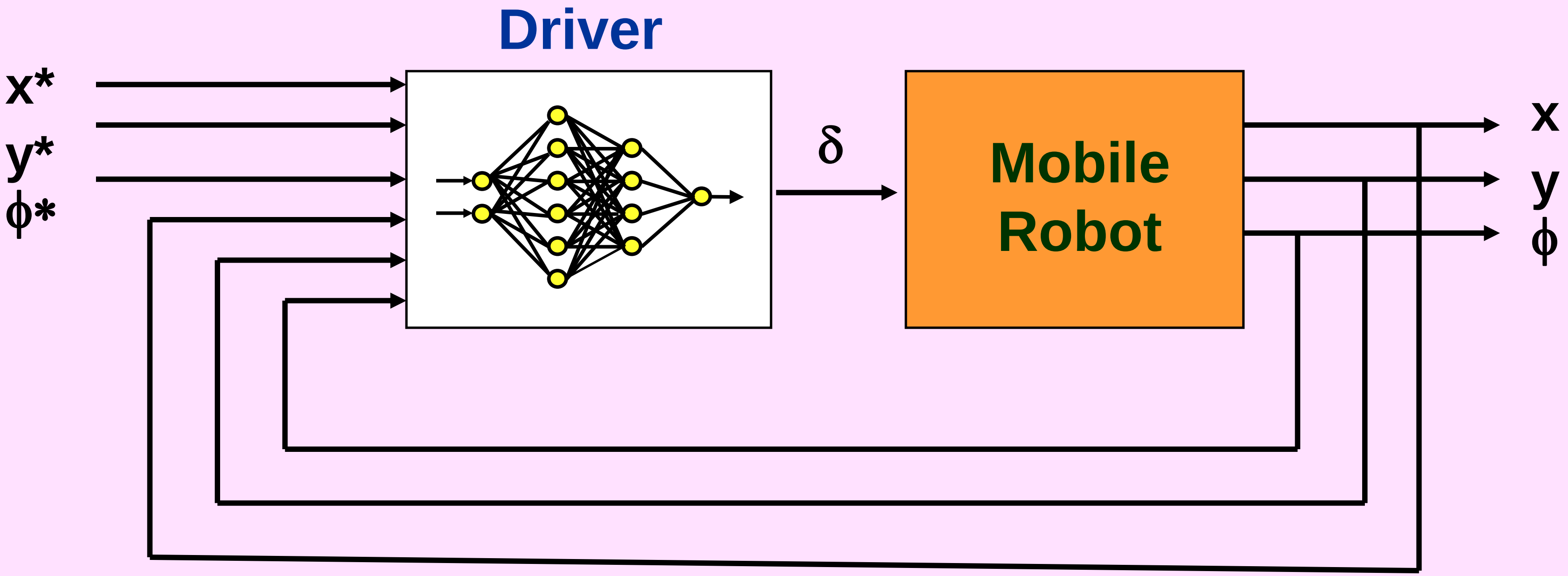
$$y(k+1) = y(k) + v\Delta t \operatorname{sen}(\phi(k))$$

$$\phi(k+1) = \phi(k) - v\Delta t / L \tan(\delta(k))$$

- Backward motion
- Constant speed
- No slipping – No skidding

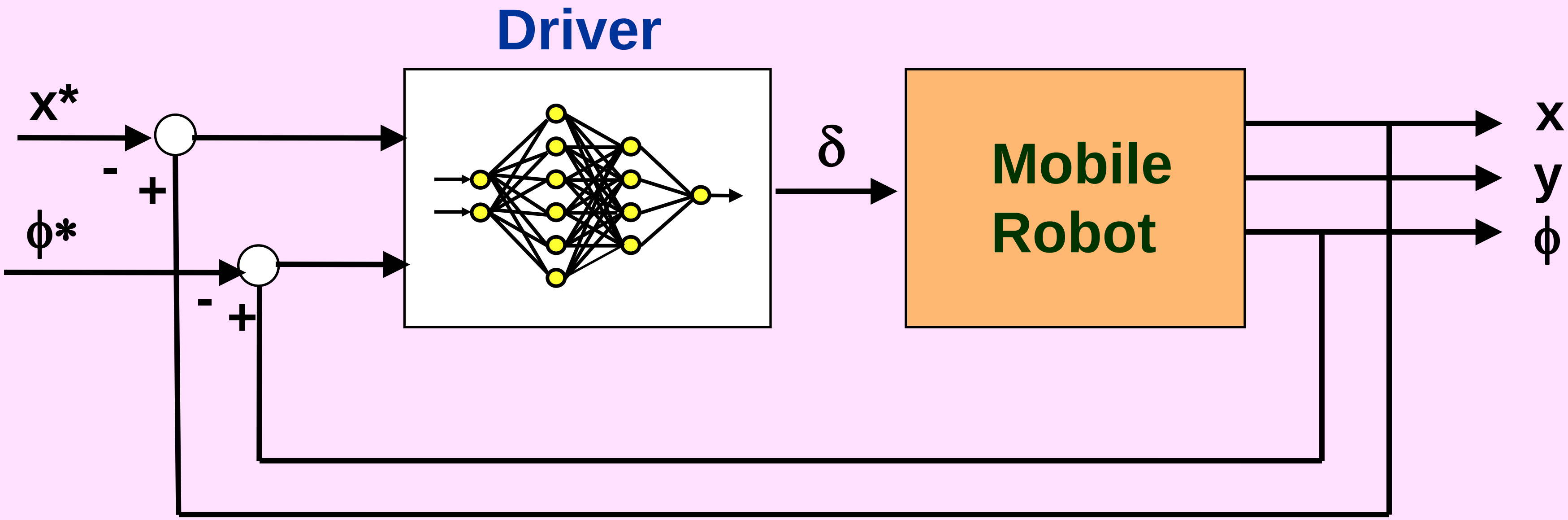
Positioning of Mobile Robot

Control Structure



Positioning of Mobile Robot

Control Structure



Given problem characteristics, coordinate y is not used for control

Dynamic Back Propagation

Robot Model

$$x(k+1) = x(k) + v\Delta t \cos(\phi(k))$$

$$\phi(k+1) = \phi(k) - v\Delta t / L \tan(\delta(k))$$

$$x_k = \begin{vmatrix} x(k) \\ \phi(k) \end{vmatrix} \qquad u_k = \tan(\delta(k))$$

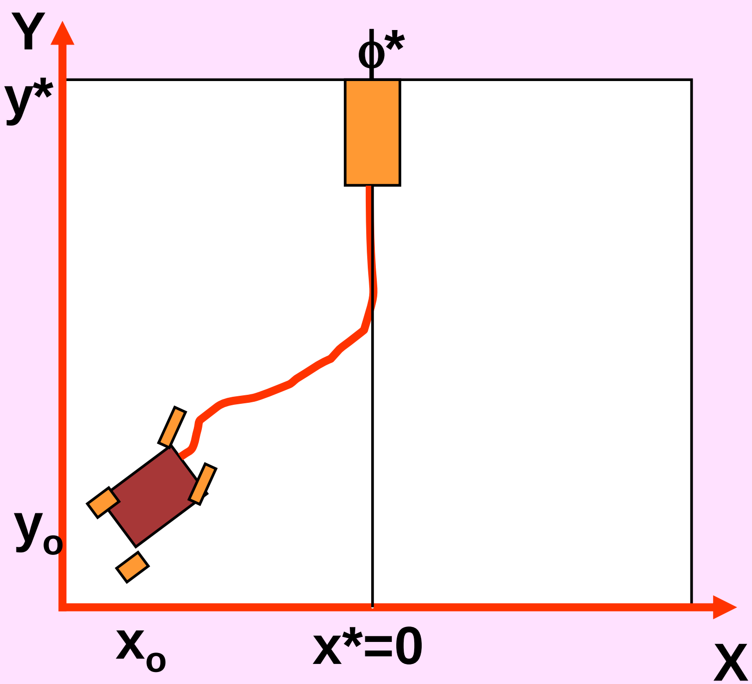
$$\frac{\overline{\partial x_{k+1}}}{\overline{\partial v}} = \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial v} + \left(\frac{\partial x_{k+1}}{\partial x_k} + \frac{\partial x_{k+1}}{\partial u_k}\frac{\partial u_k}{\partial x_k}\right)\frac{\overline{\partial x_k}}{\overline{\partial v}}$$

Computed with the system model

$$\frac{\partial x_{k+1}}{\partial x_k} = \begin{vmatrix} 1 & -v\Delta t \sin(\phi(k)) \\ 0 & 1 \end{vmatrix}$$

$$\frac{\partial x_{k+1}}{\partial u_k} = \begin{vmatrix} 0 \\ -v\Delta t/L \end{vmatrix}$$

Incremental Learning



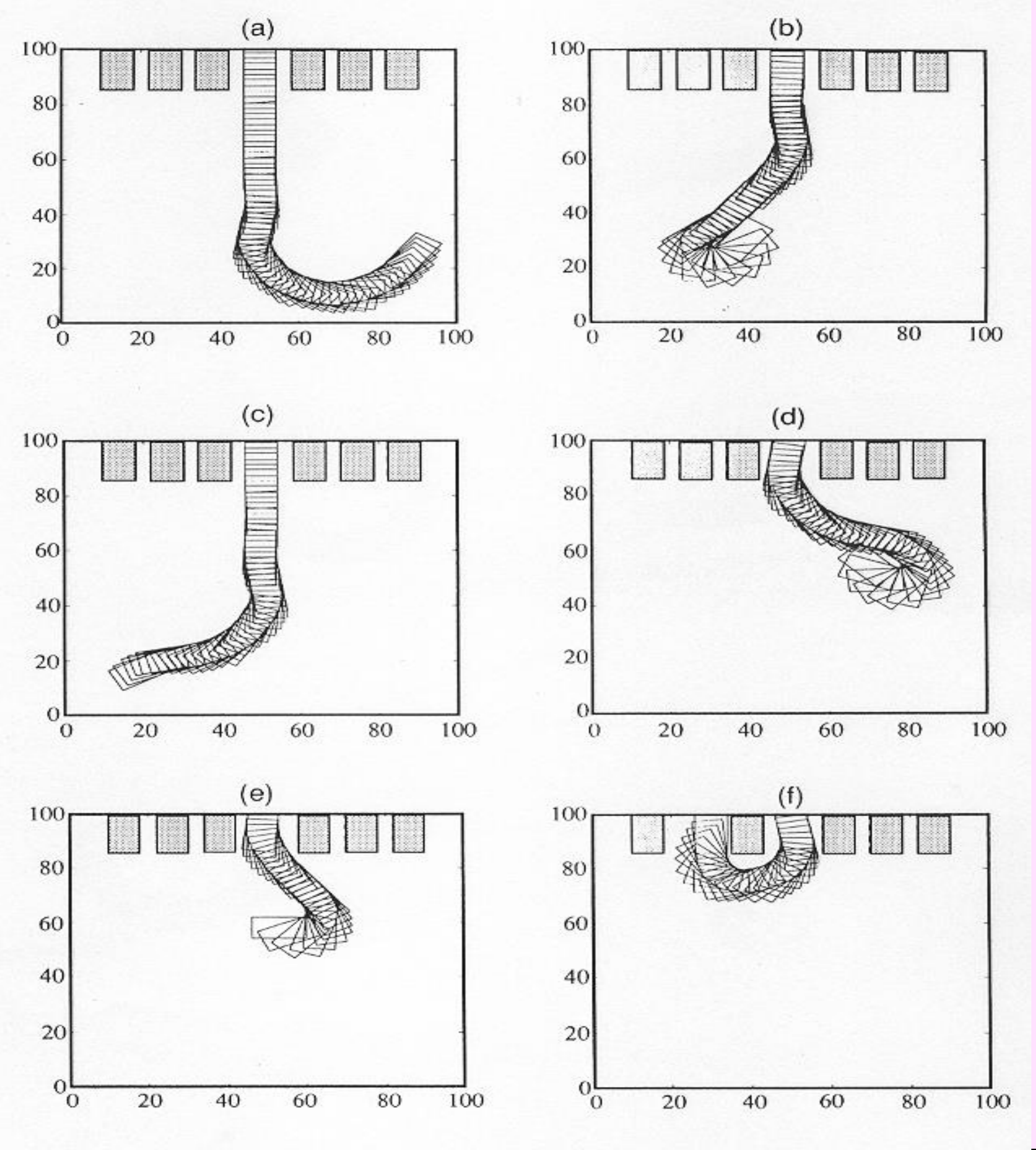
Train the neural network for positions close to $x^*=0$ (four positions)

- $x = \; -2 \quad -2 \quad 2 \quad 2$
  $\phi = \; -\pi/2 \quad \pi/2 \quad -\pi/2 \quad \pi/2$

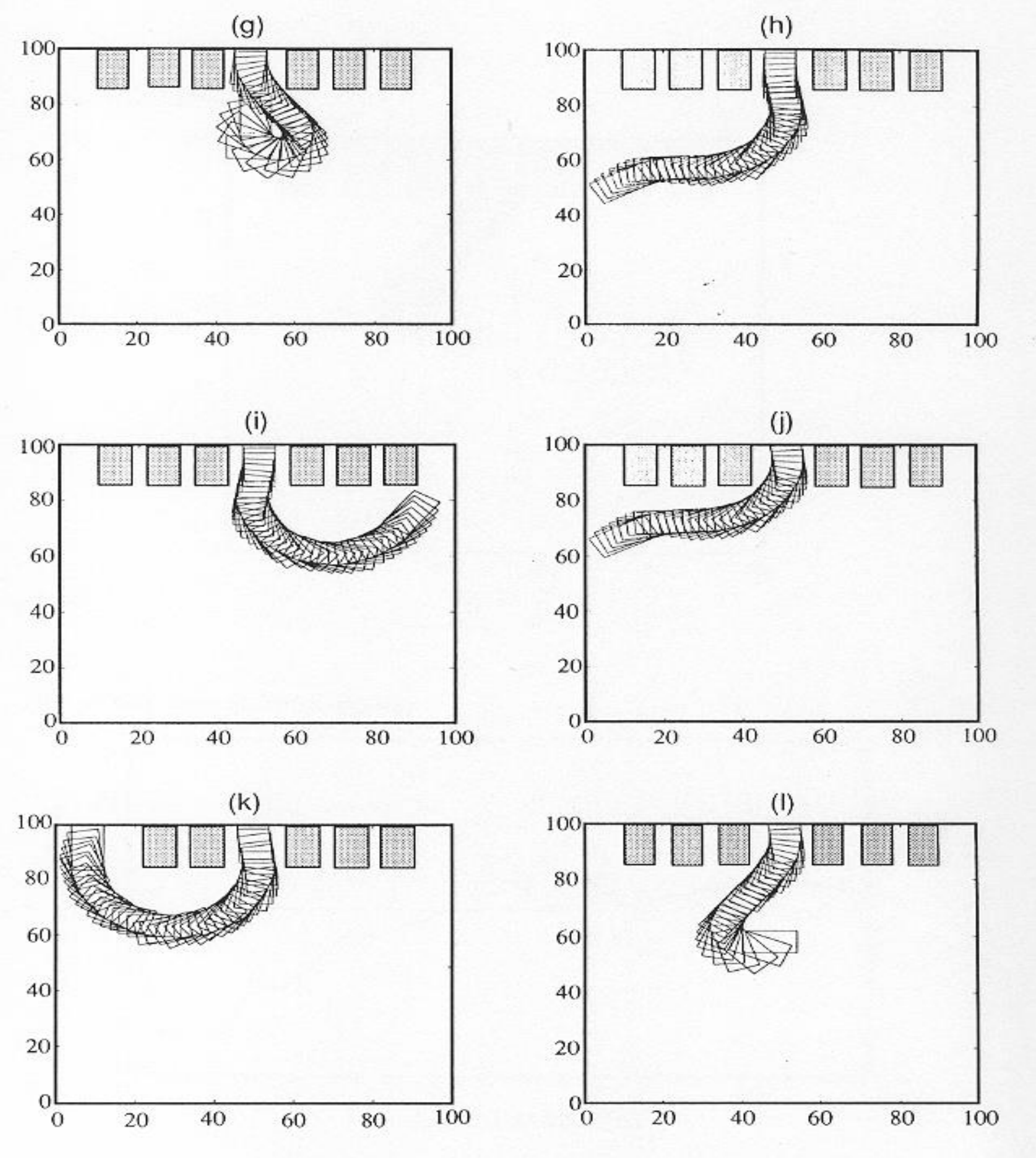
Train the neural network for far away positions

- $x = \; -4 \quad -4 \quad 4 \quad 4$
  $\phi = \; -\pi/2 \quad \pi/2 \quad -\pi/2 \quad \pi/2$
- $x = \; -6 \quad -6 \quad 6 \quad 6$
  $\phi = \; -\pi/2 \quad \pi/2 \quad -\pi/2 \quad \pi/2$

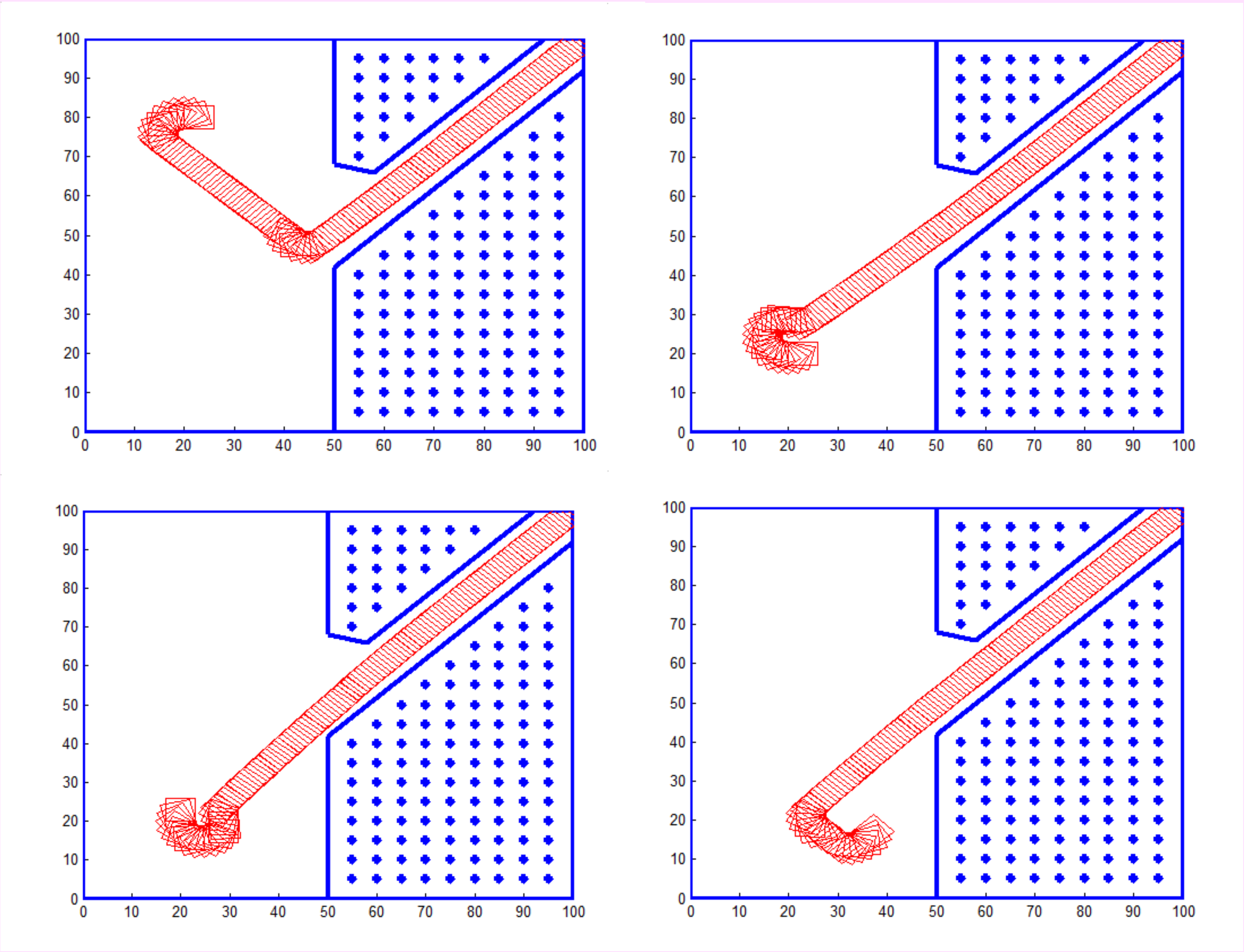
Trajectories of Mobile Robot to Achieve a Final Desired Position



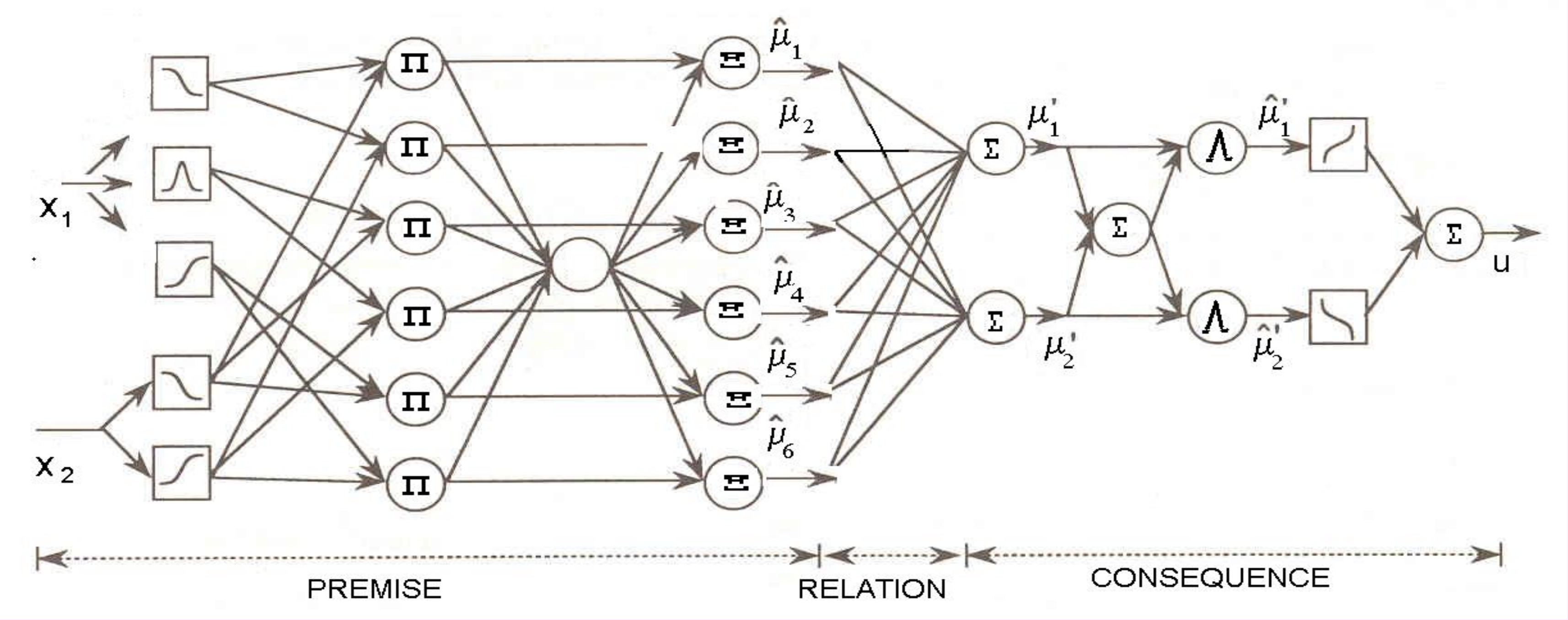
Trajectories of Mobile Robot to Achieve a Final Desired Position



Trajectories of Mobile Robot to Follow a Road



Fuzzy Neural Network

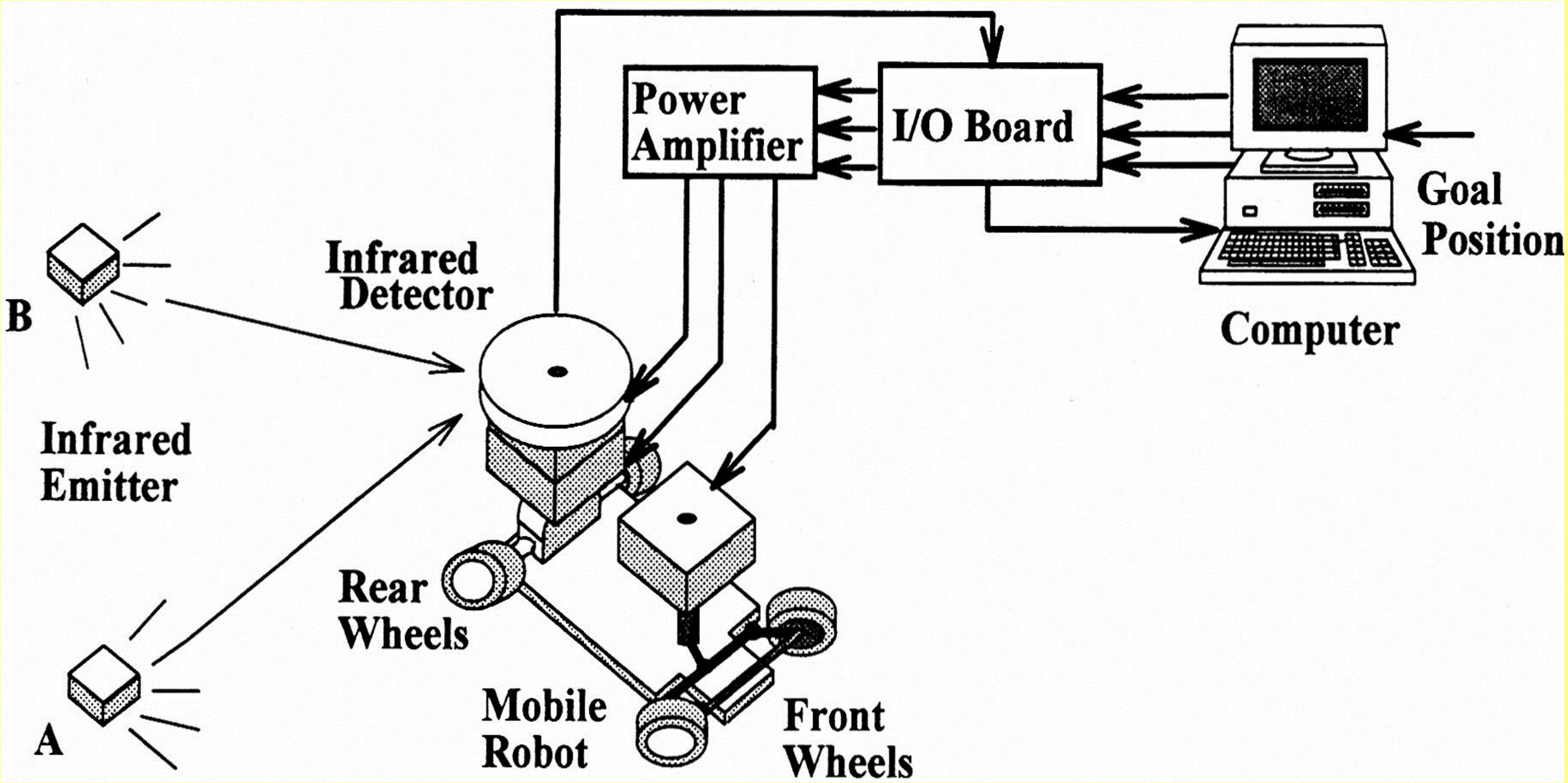


Integrates:

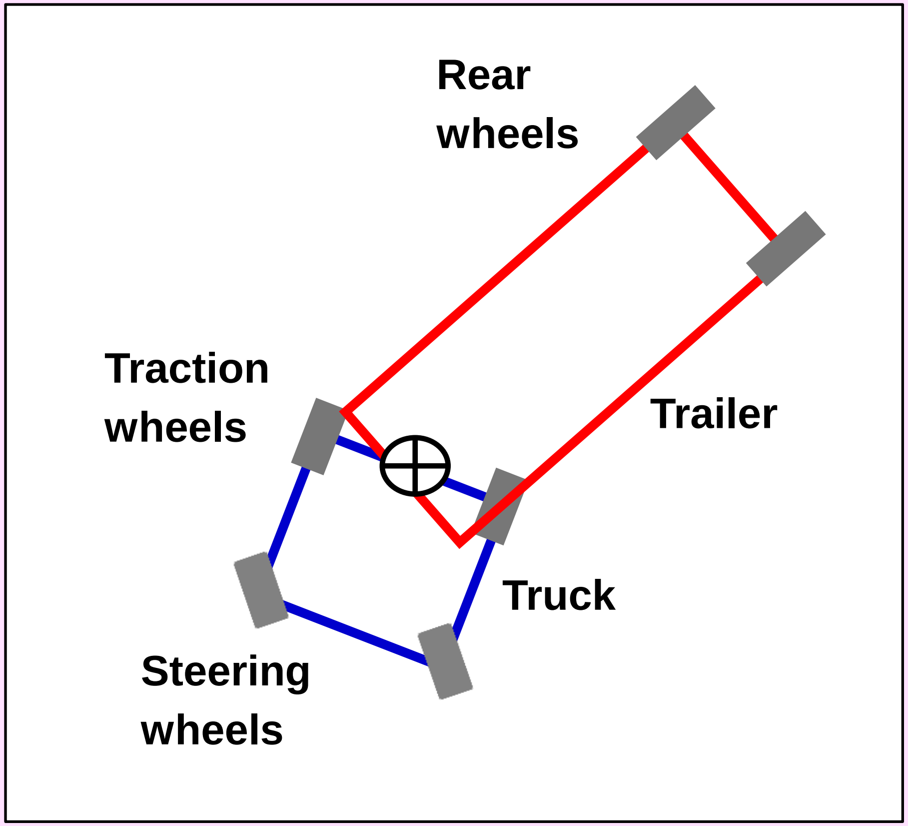
Knowledge → **IF -THEN Rules (Fuzzy)**

Data → **Training (Neural Network)**

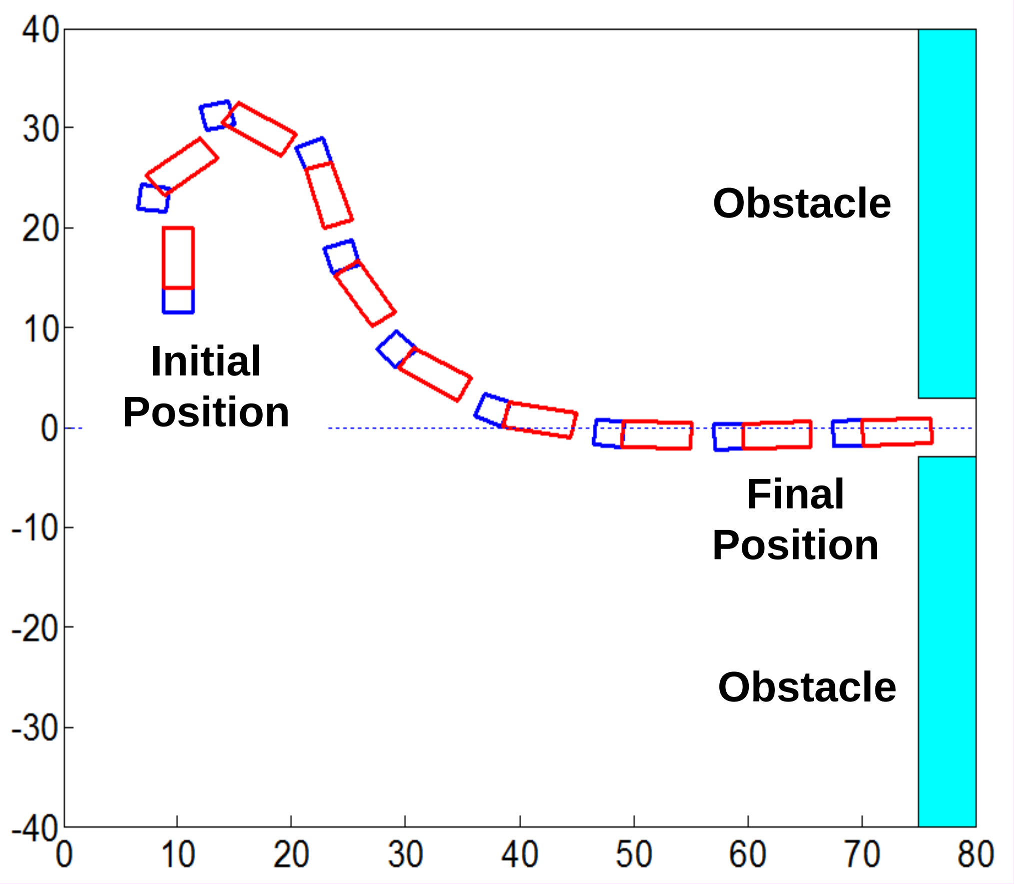
Experimental Mobile Robot



Control of a Truck-Trailer Mobile Robot

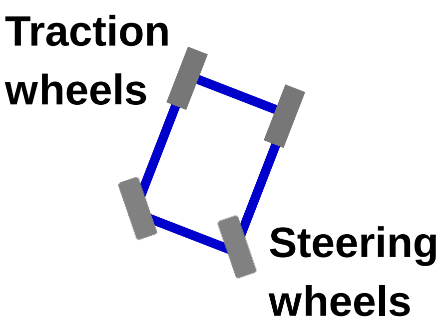


Control of a Truck-Trailer Mobile Robot

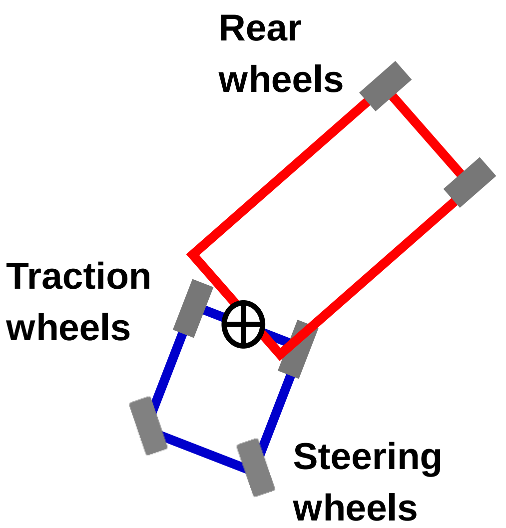


Incremental Learning

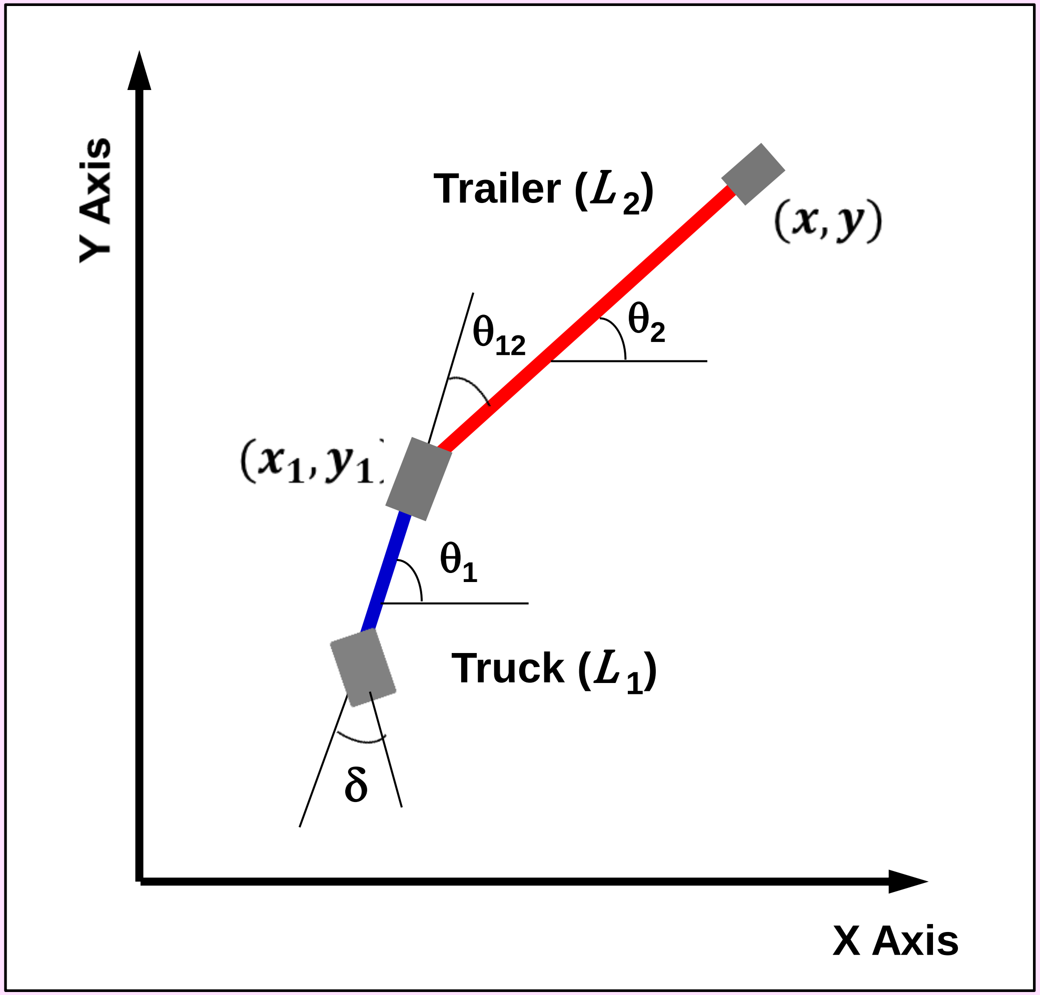
- **Train the neural network for controlling a car $\theta_{12} = 0$**
  - **Close to the desired position**
  - **Away from the desired position**



- **Train the neural network for controlling a truck-trailer $\theta_{12} \neq 0$**
  - **Small values of θ_{12}**
  - **Higher values of $\theta_{12} < \pi/2$**



Control of a Truck-Trailer Mobile Robot



$$\dot{x} = v \cos\theta_{12} \cos\theta_2$$

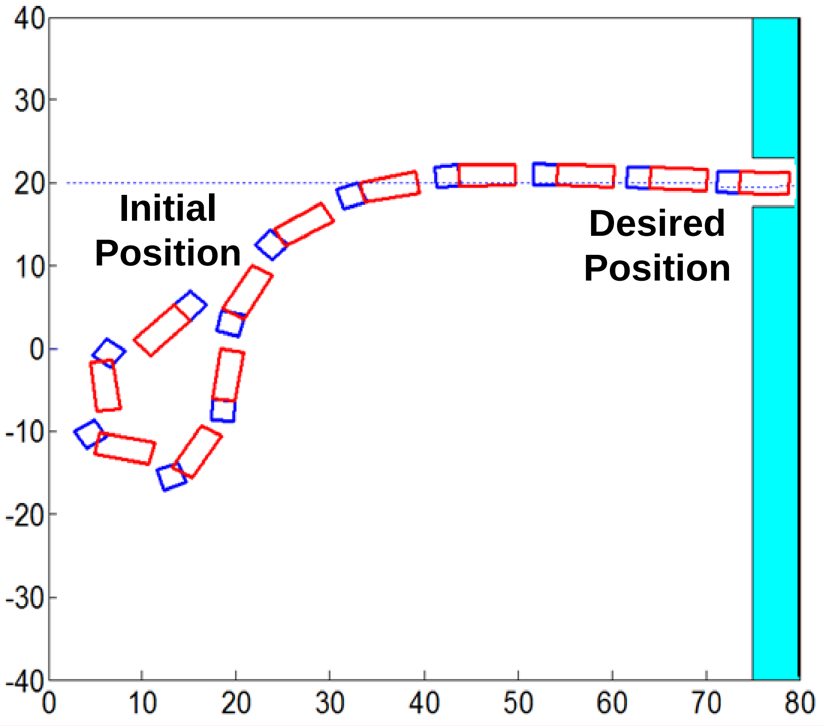
$$\dot{y} = v \cos\theta_{12} \sin\theta_2$$

$$\dot{\theta}_1 = -\frac{v}{L_1} \tan\delta$$

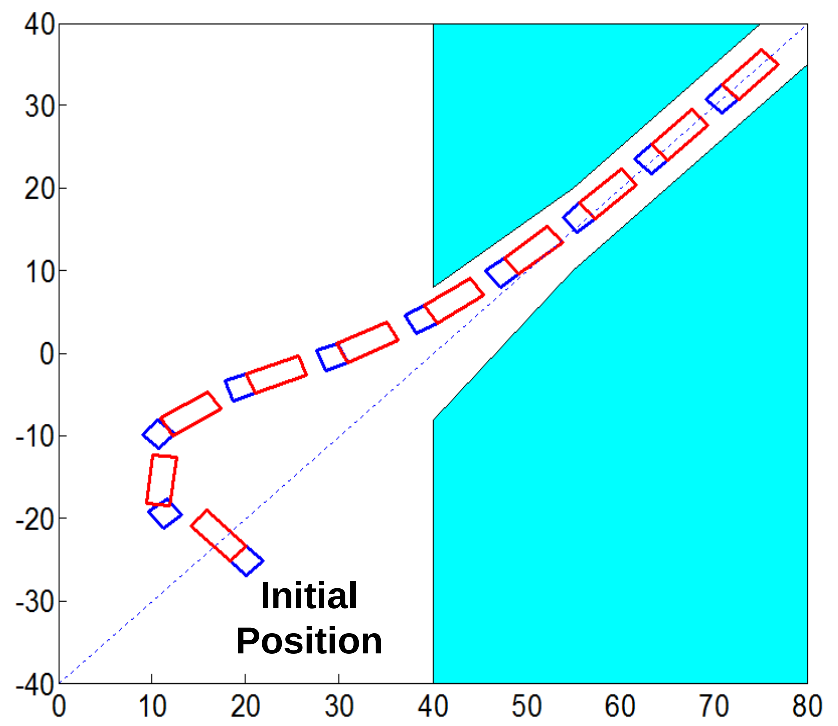
$$\dot{\theta}_2 = -\frac{v}{L_2} \sin\theta_{12}$$

Control of a Truck-Trailer Mobile Robot

Achieving a Goal Position

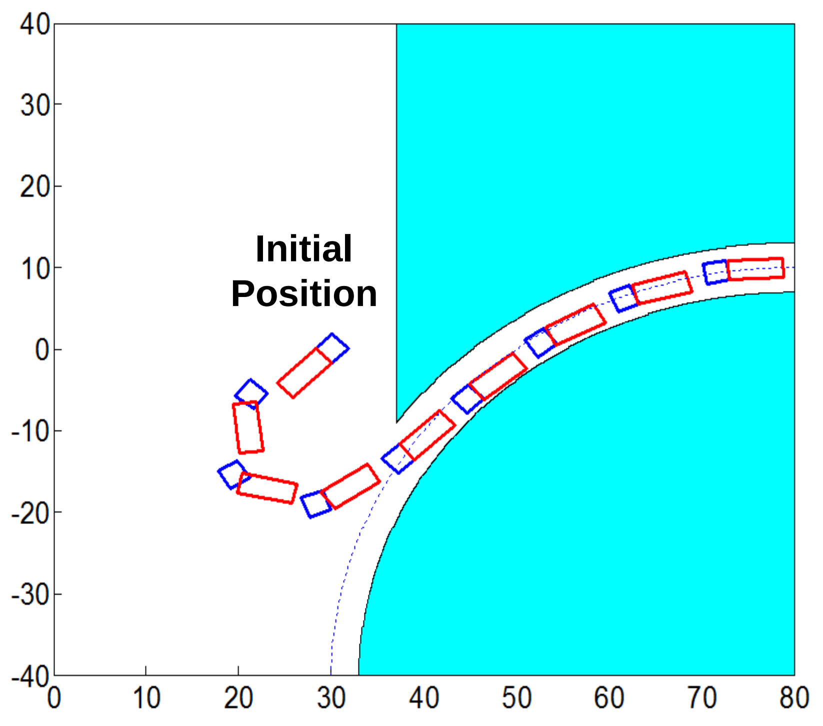


Following a Straight Line

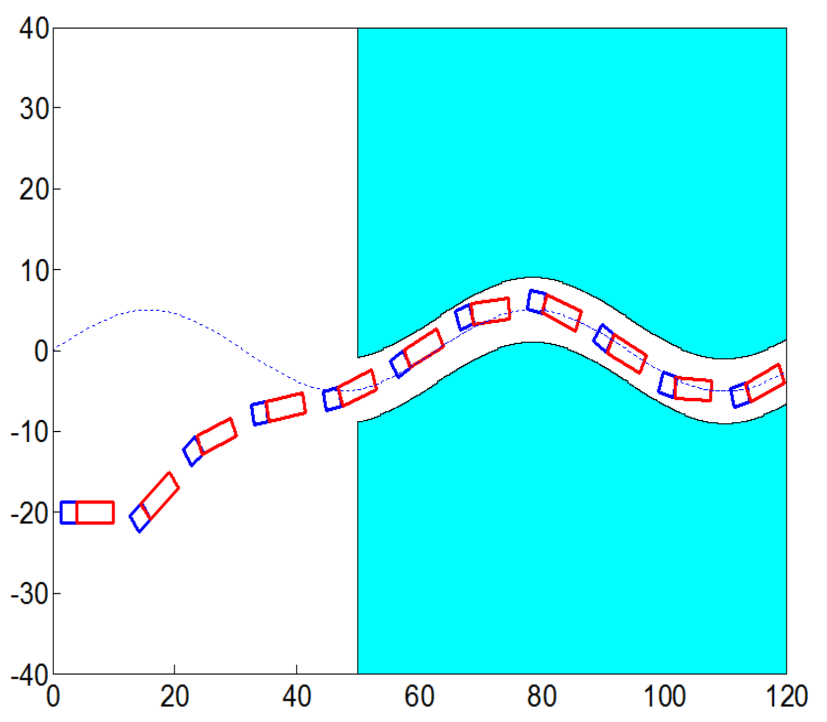


Control of a Truck-Trailer Mobile Robot

Following a Curved Path



Following a Sinusoidal Path



Thank you for your attention!

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