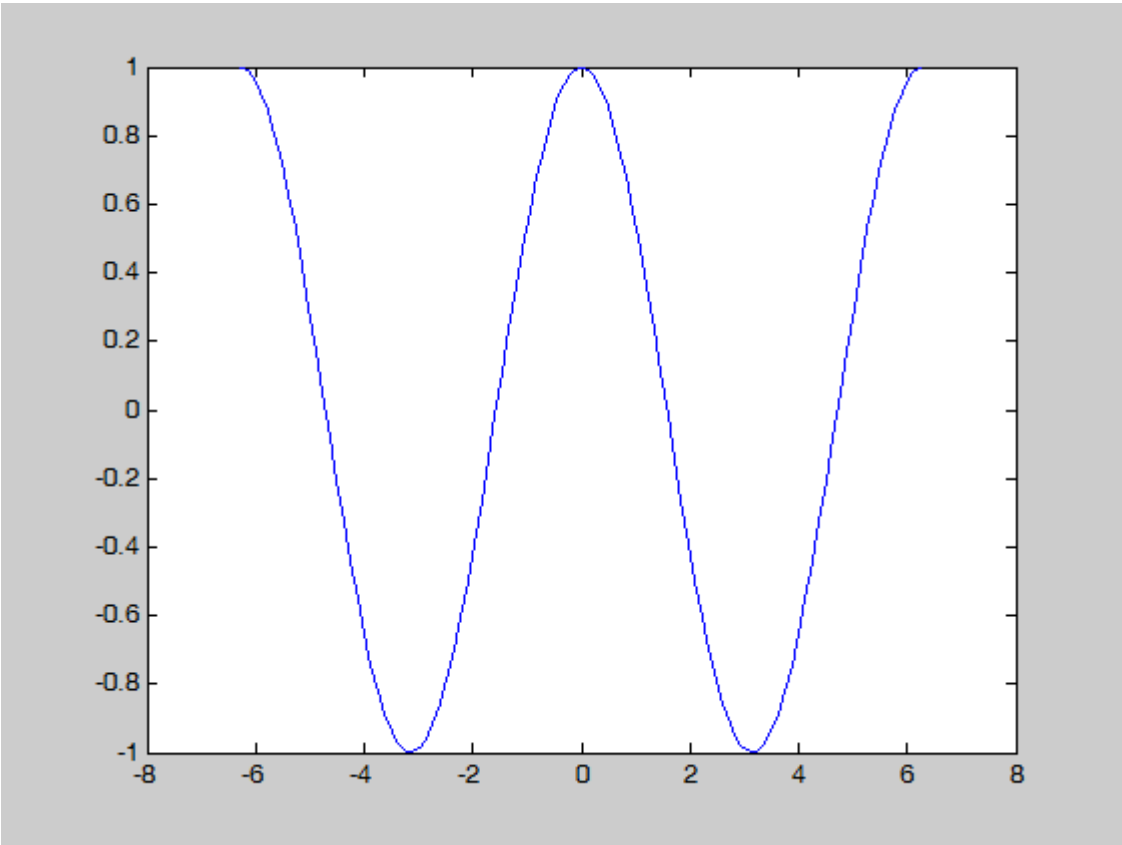


# Data driven function approximation

# Plot1d

Plot an arbitrary one-dimensional function

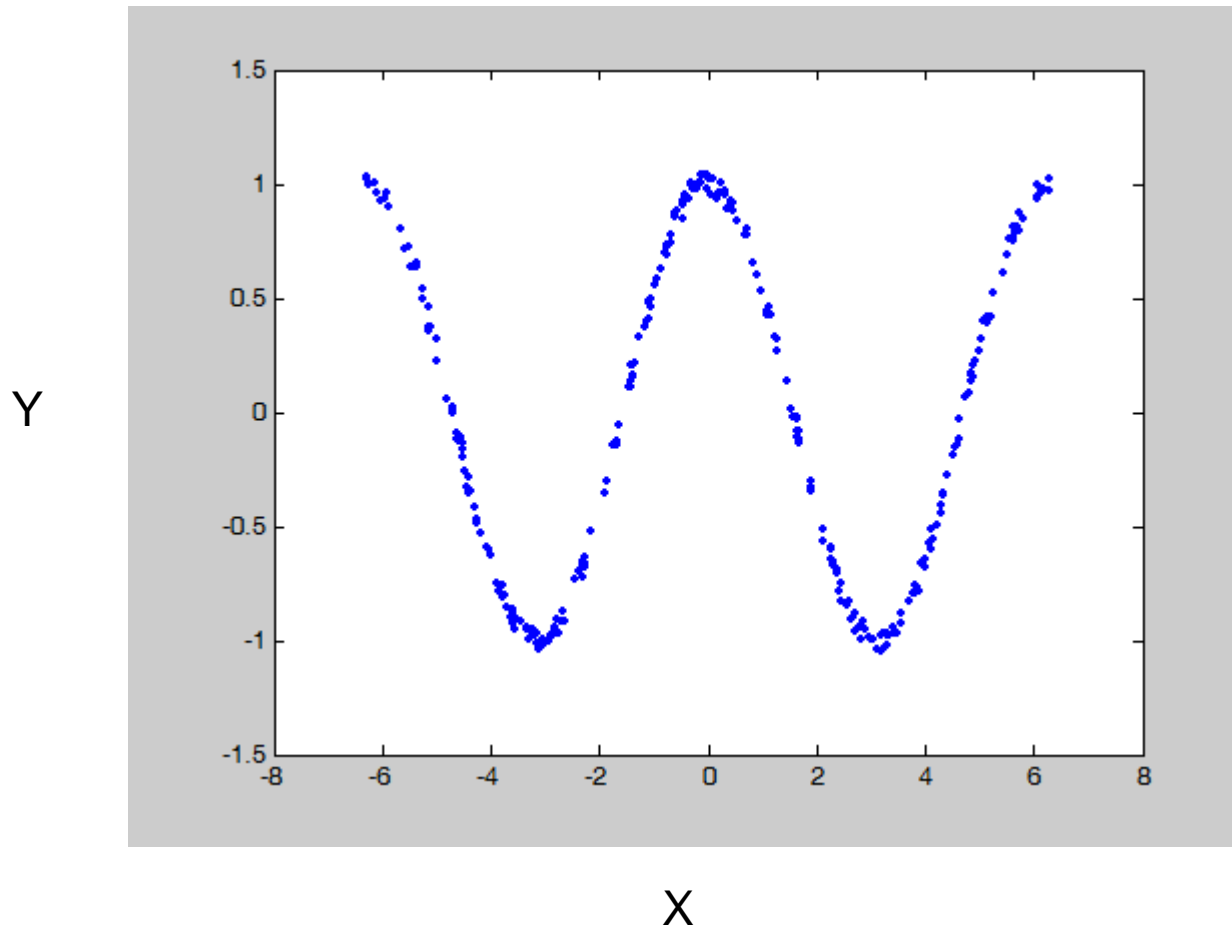
```
clear all
fstr=input('input a function: x.^2+cos(x) :','s');
fx=inline(fstr);
range=2*pi;
x=linspace(-range,range);
y=fx(x);
max_y=max(abs(y));
plot(x,y/max_y);
hold on;
```



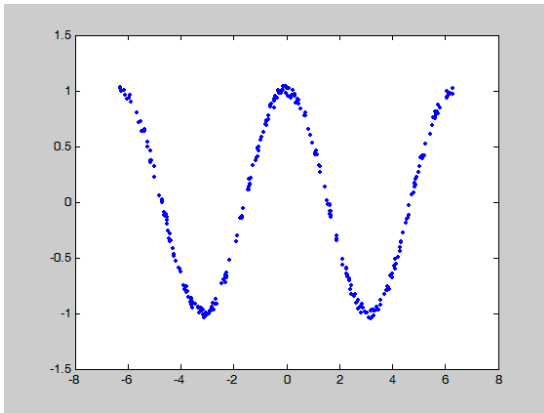
# Sampling

```
N=input('keyin sample size:');  
x=rand(1,N)*2*range-range;  
n=rand(1,N)*0.1-0.05;  
y=fx(x)/max_y+n;  
figure  
plot(x,y, '.');
```

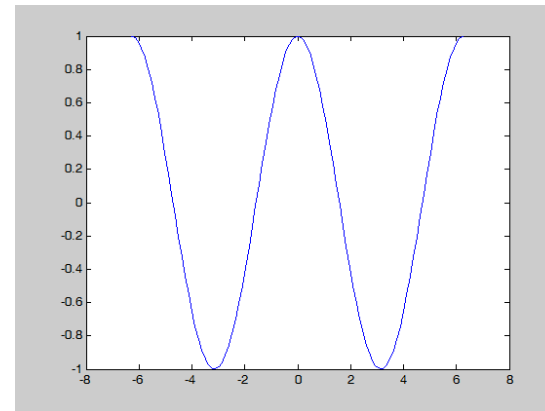
# Paired data



# Function Approximation



DDFA

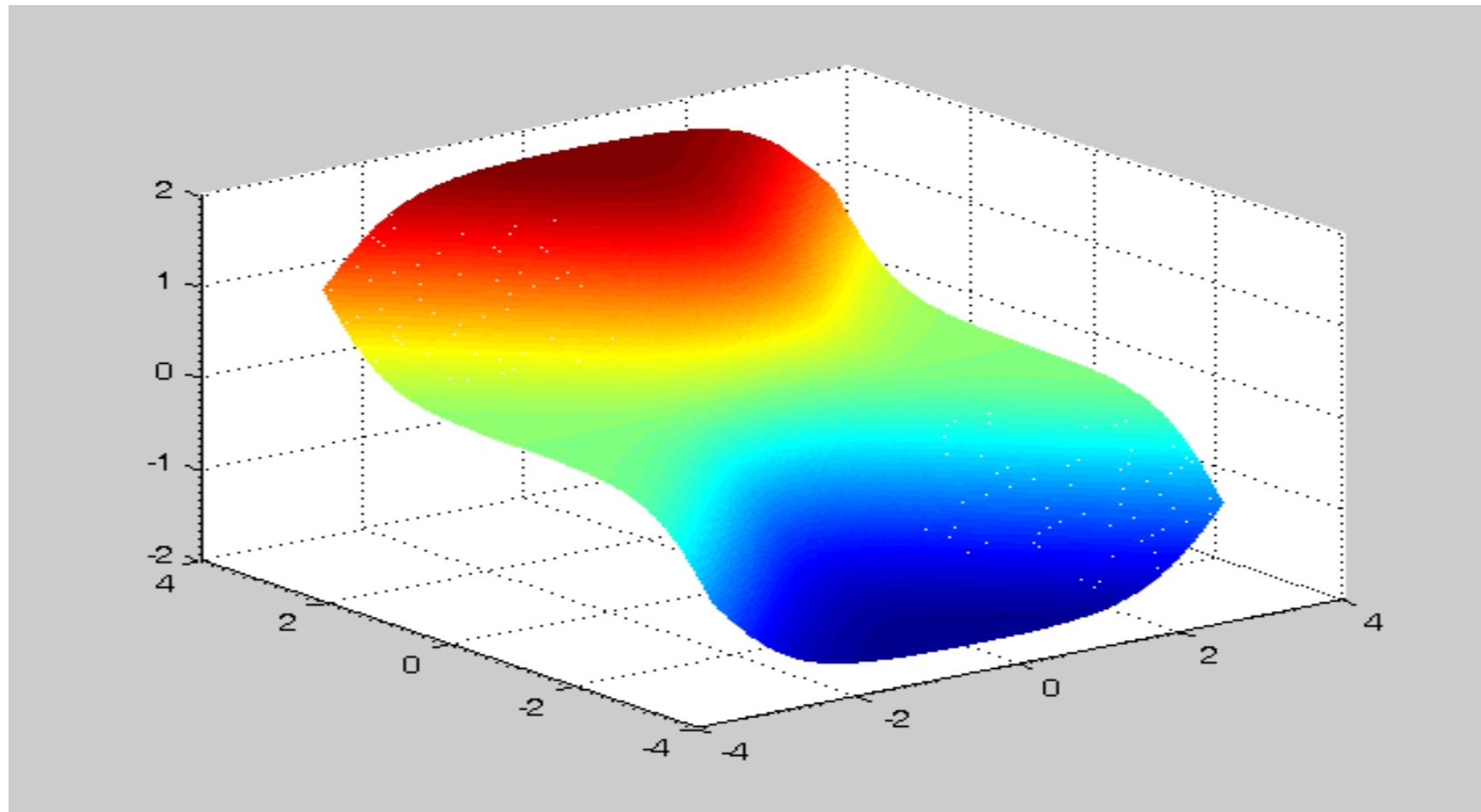


# Plot2d

- Plot an arbitrary two-dimensional function

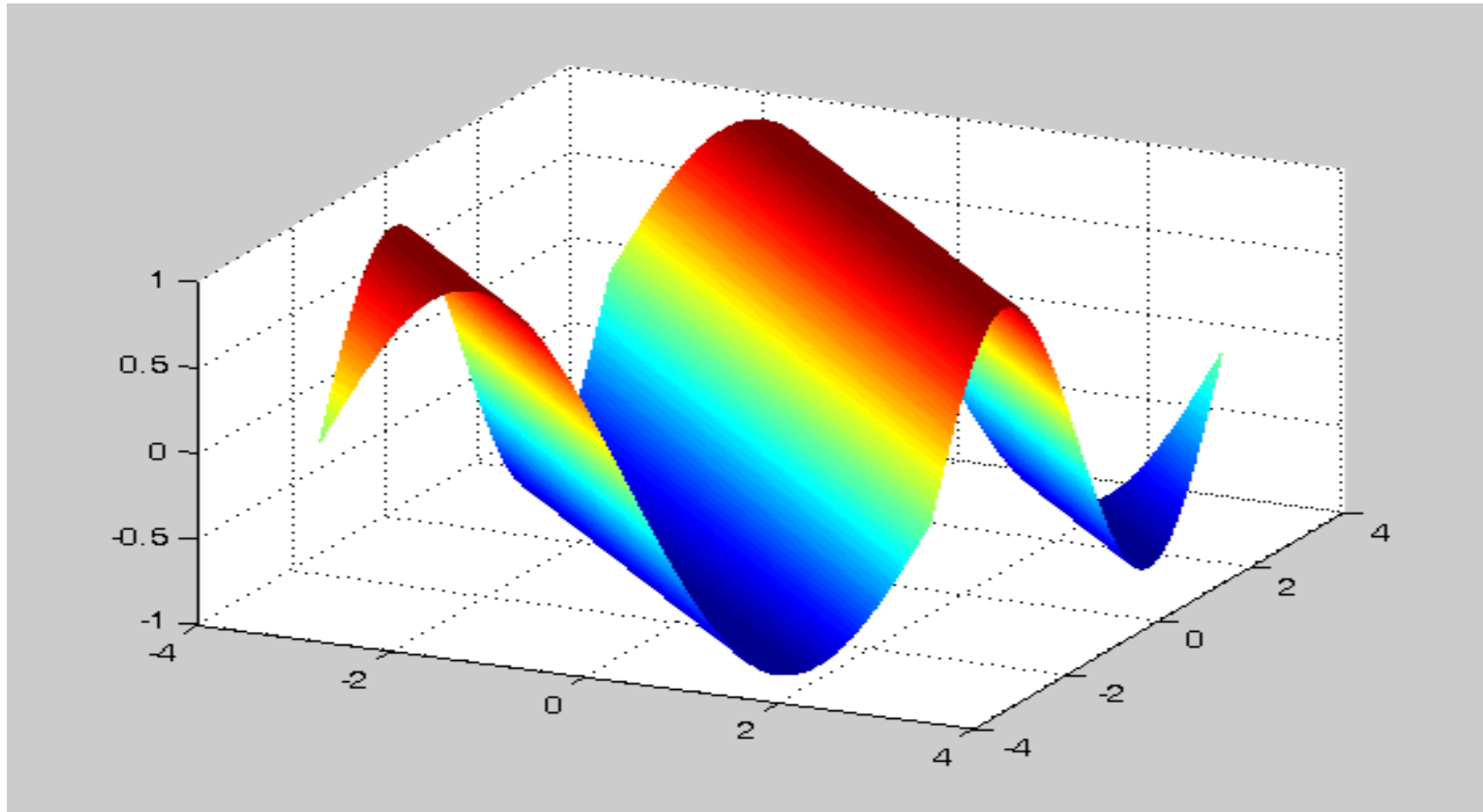
```
fstr=input('input a 2D function: x1.^2+x2.^2+cos(x1) :','s');
fx=inline(fstr);
range=pi;
x1=-range:0.02:range;
x2=x1;
for i=1:length(x1)
    C(i,:)=fx(x1(i),x2);
end
mesh(x1,x2,C);
hold on;
```

$$\tanh(x_1+x_2)+\tanh(x_1-x_2)$$





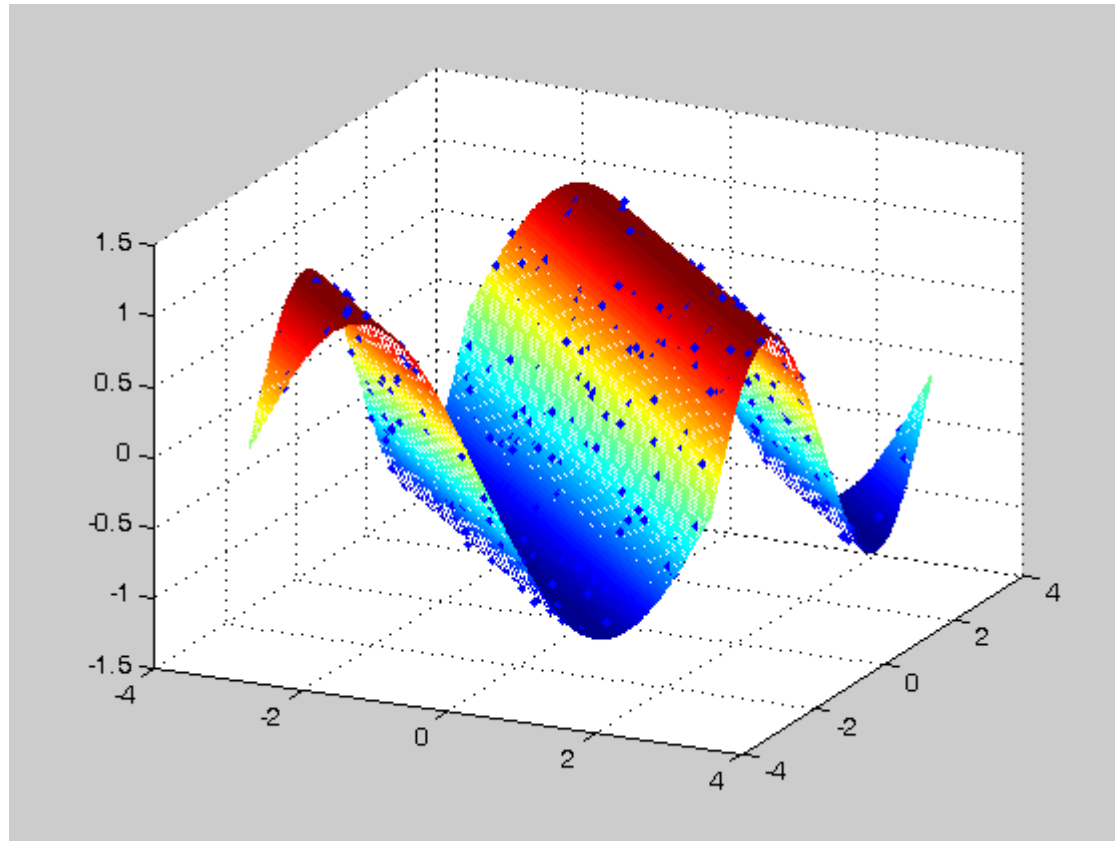
$\sin(x_1+x_2)$



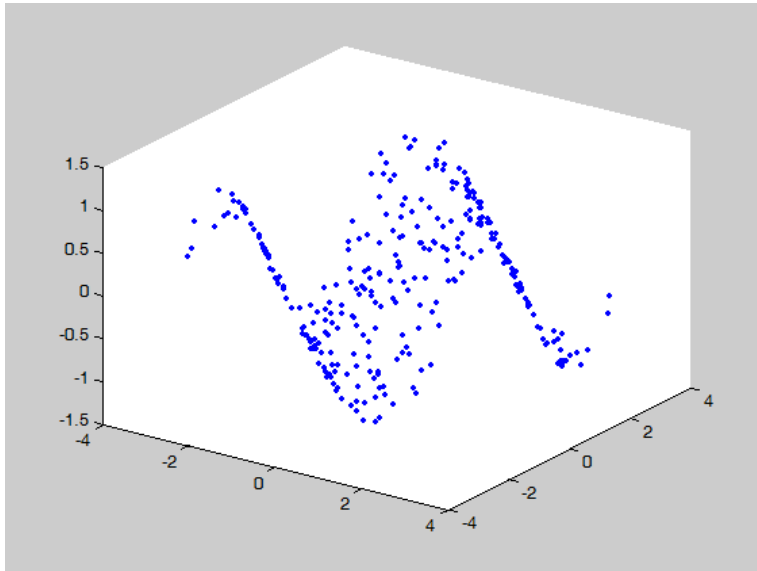
# Sampling

```
N=input('keyin sample size:');  
x(1,:)=rand(1,N)*2*range-range;  
x(2,:)=rand(1,N)*2*range-range;  
n=rand(1,N)*0.1-0.05;  
y=fx(x(1,:),x(2,:))+n;  
plot3(x(2,:),x(1,:),y, '.');
```

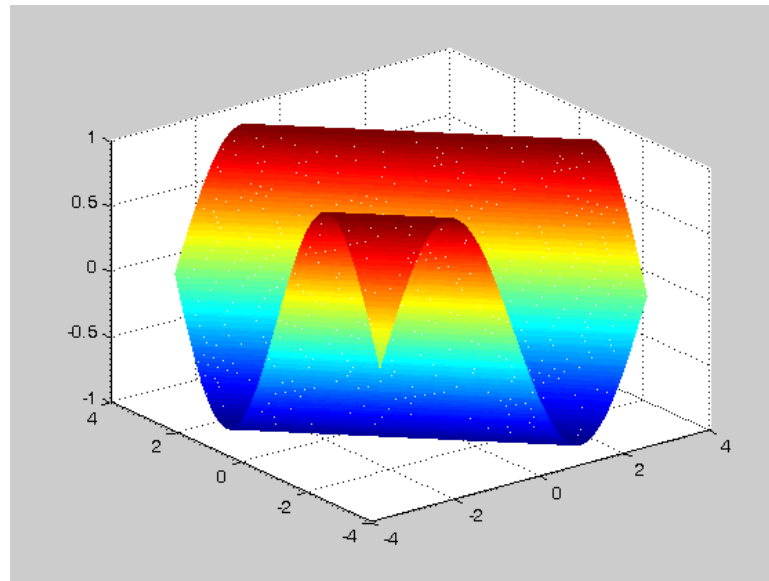
# Sampling



# Function guessing



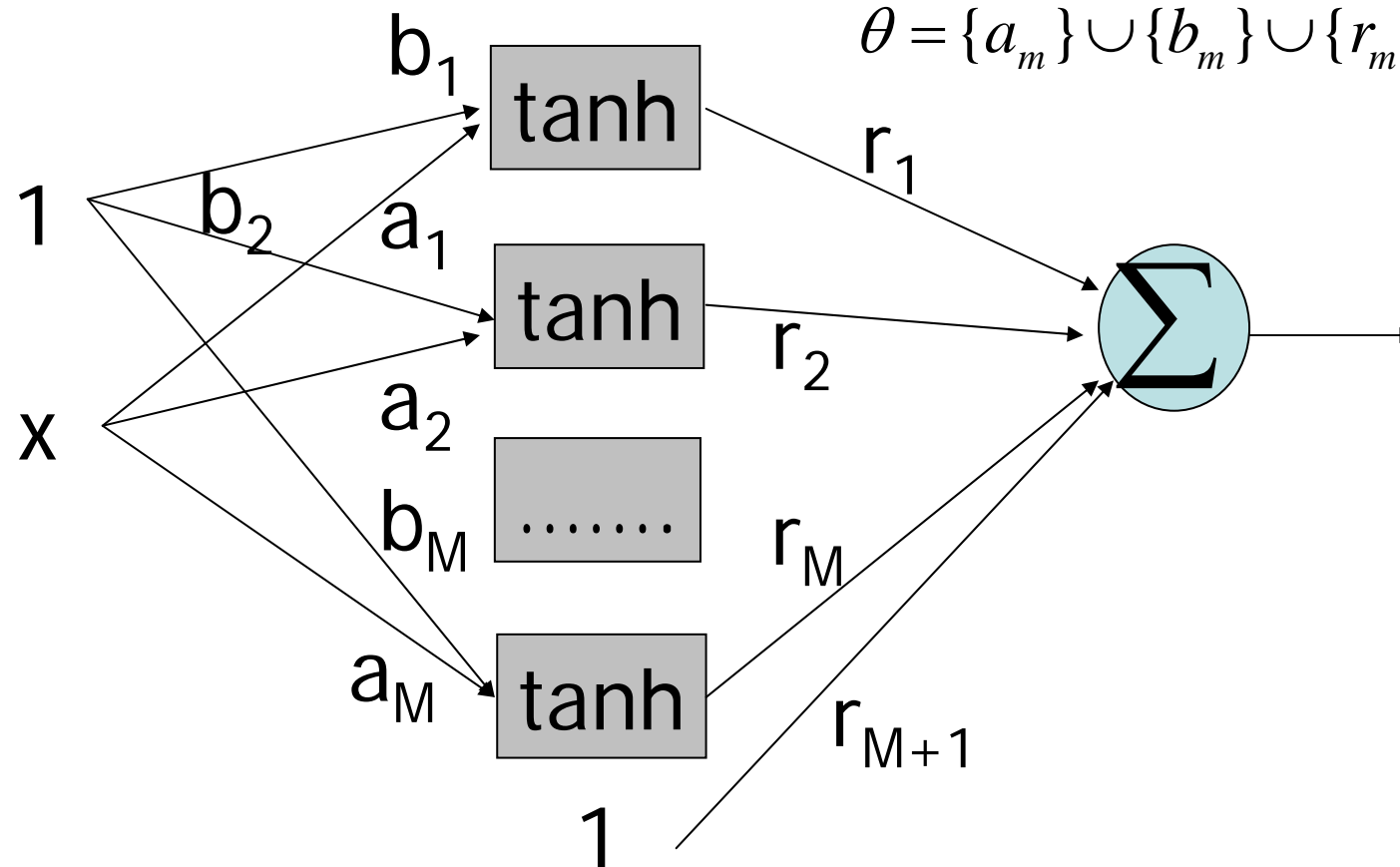
DDFA



# Neural Networks

$$f(x_i; \theta) = \sum_{m=1}^M r_m \tanh(a_m x + b_m) + r_0$$

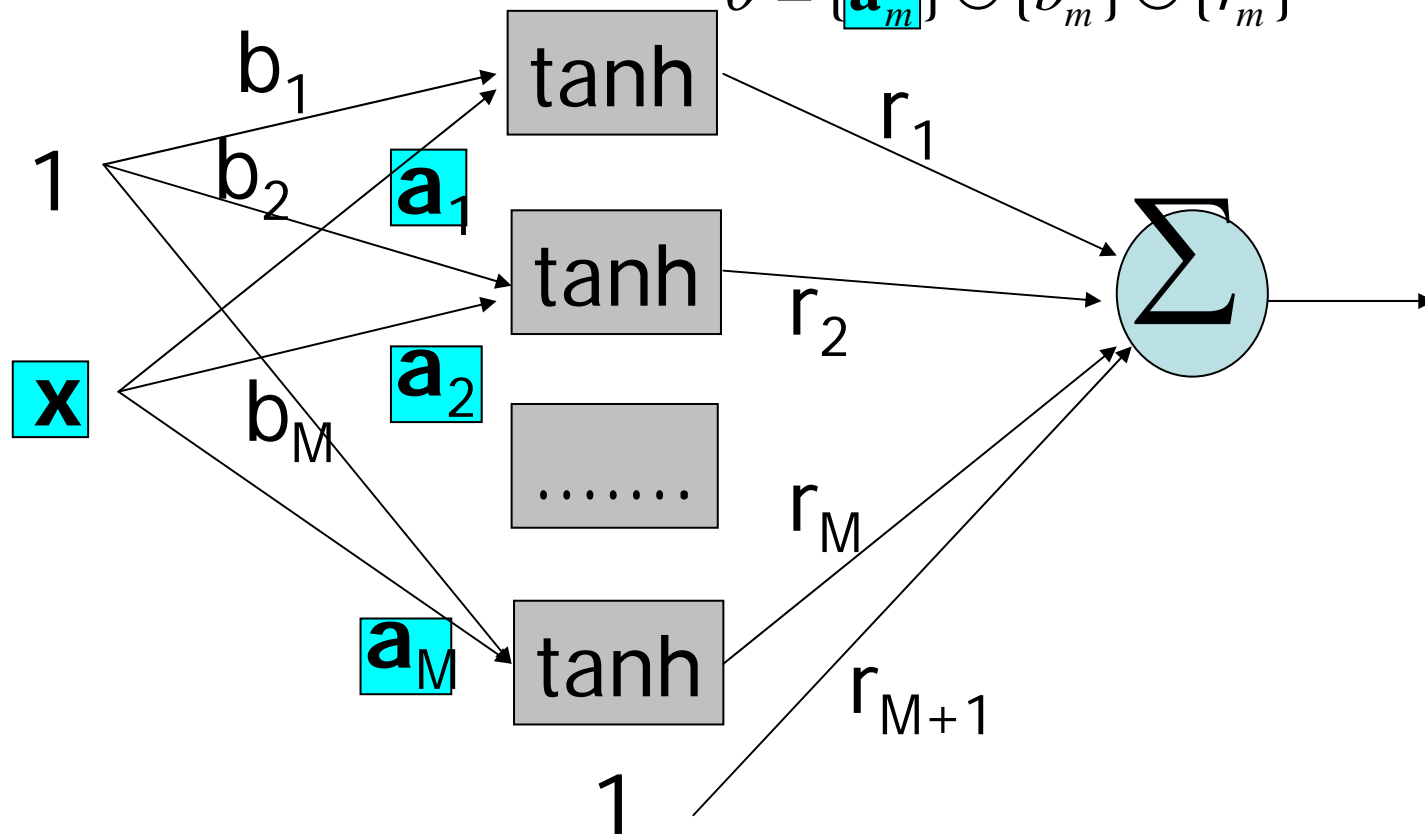
$$\theta = \{a_m\} \cup \{b_m\} \cup \{r_m\}$$



# Neural Networks

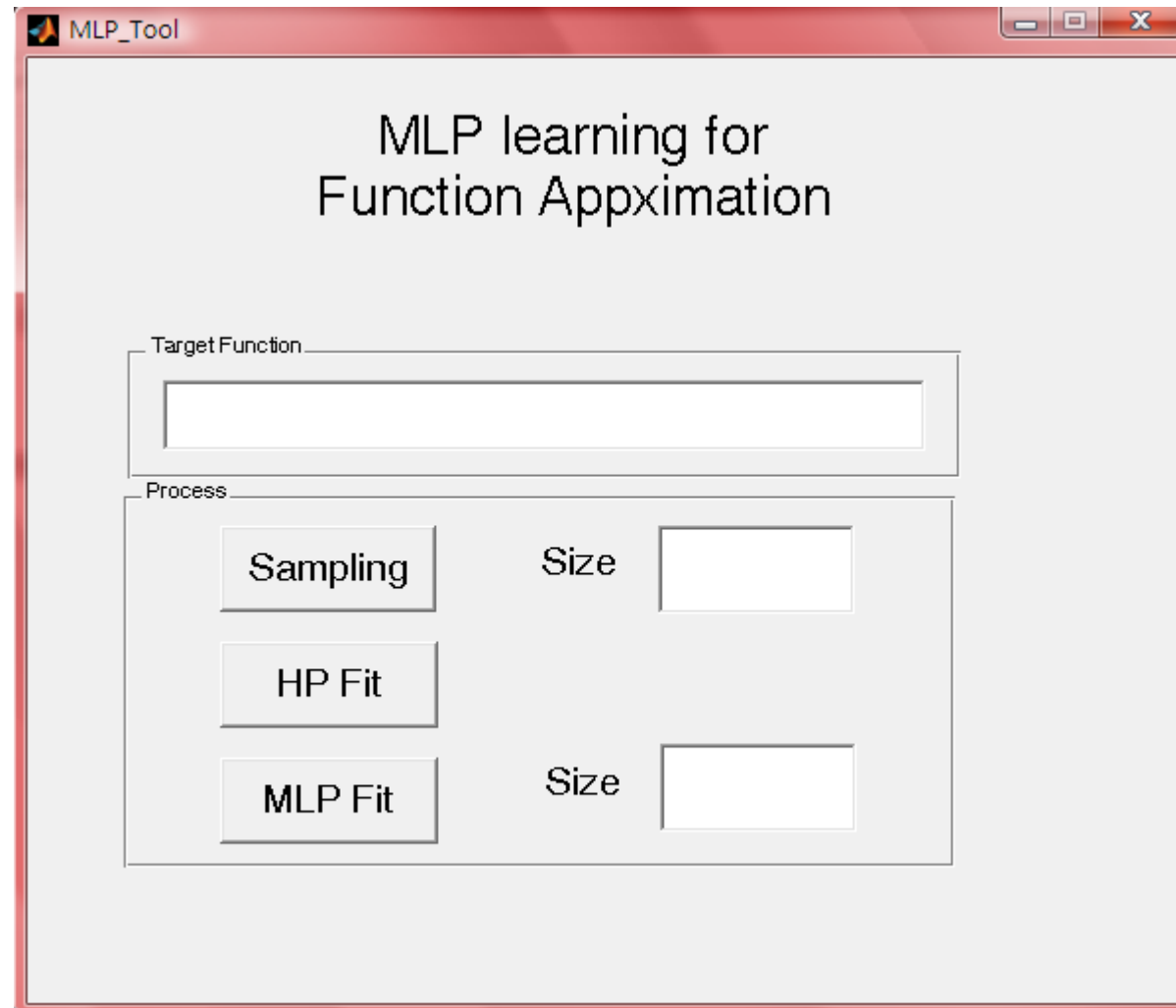
$$f(x_i; \theta) = \sum_{m=1}^M r_m \tanh(\mathbf{a}_m^T \mathbf{x} + b_m) + r_0$$

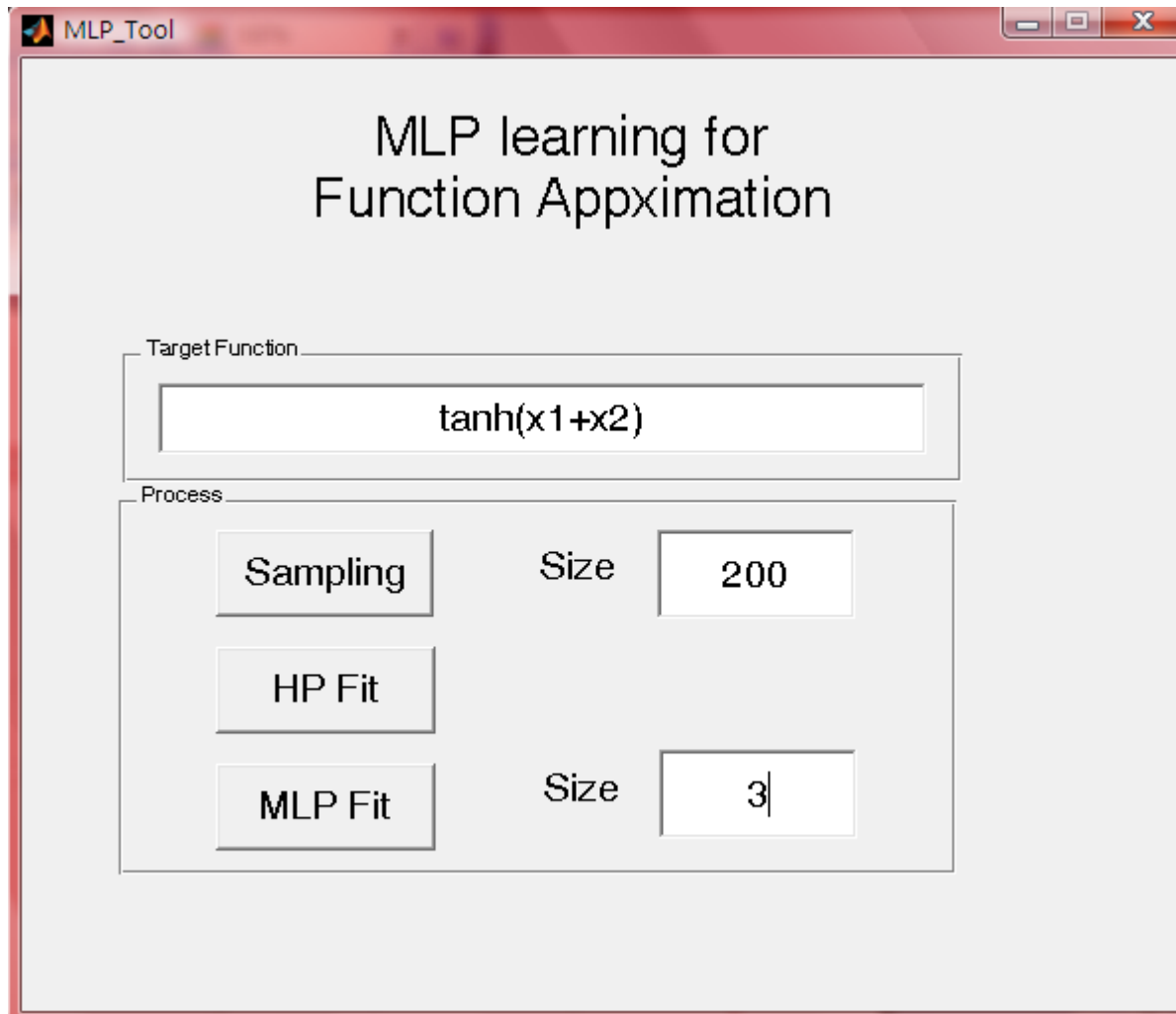
$$\theta = \{\mathbf{a}_m\} \cup \{b_m\} \cup \{r_m\}$$



[MLP\\_Tool.fig](#)

[MLP\\_Tool.m](#)







# Mapping

1. Head: function  $y = \text{eval\_MLP2}(x, r, a, b)$

2. Body:

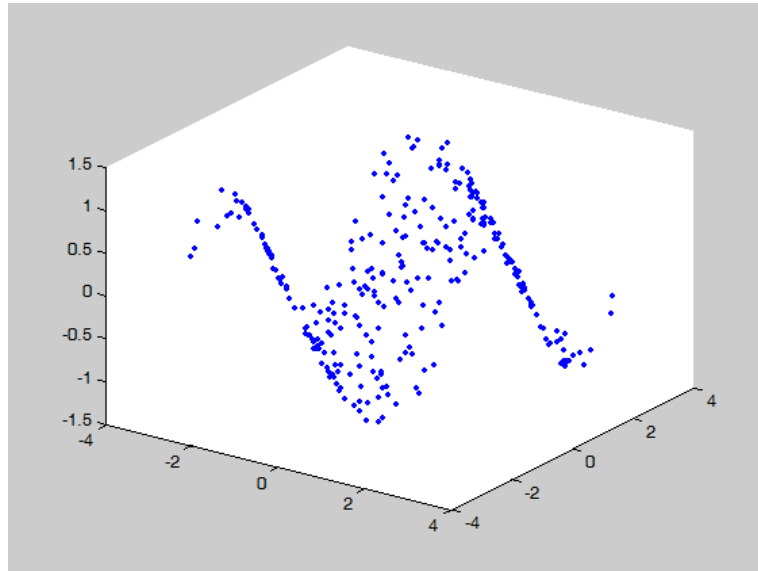
$M = \text{size}(a, 1)$

$y = r(M+1)$

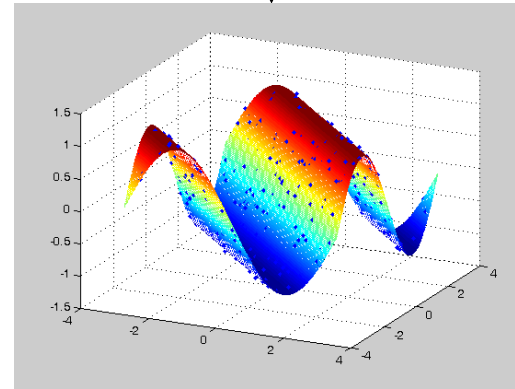
for  $m = 1:M$

    Add  $r(m) * \tanh(a(m,:) * x + b(m))$  to  $y$

# Function Riddle



DDFA



$(\mathbf{x}_i, y_i), i = 1, \dots, n,$

$\mathbf{x}_i \in R^d$

$$E(r, a, b) = \frac{1}{n} \sum_{i=1}^n (y_i - f(\mathbf{x}_i; r, a, b))^2$$

# MLP learning

```
[a,b,r]=learn_MLP2(x',y',M);
```

MLP learning

# High-dimensional function approximation

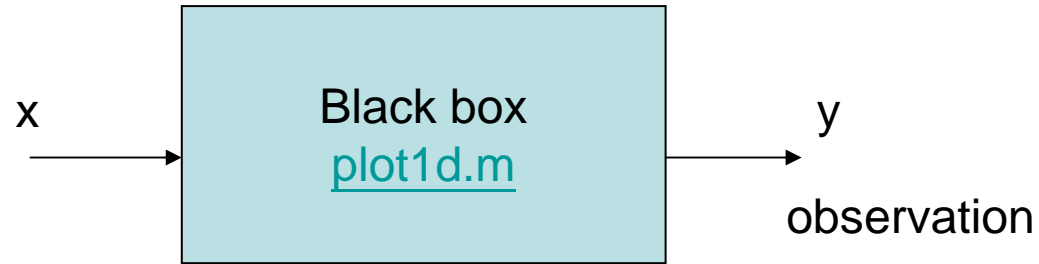
[The NNSYSID Toolbox](#)

1	<u><a href="#">eval_MLP2.m</a></u>	Evaluate MLP function
2	<u><a href="#">mean_square_error2.m</a></u>	Calculate E
3	<u><a href="#">learn_MLP.m</a></u>	Seek parameters

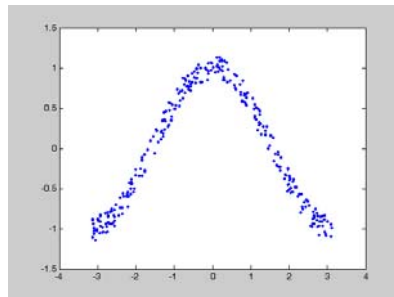
# One-dimensional function approximation

1	<a href="#"><u>eval_MLP.m</u></a>	Evaluate an MLP function
2	<a href="#"><u>mean_square_error2.m</u></a>	Calculate E
3	<a href="#"><u>learn_MLP.m</u></a>	Seek parameters

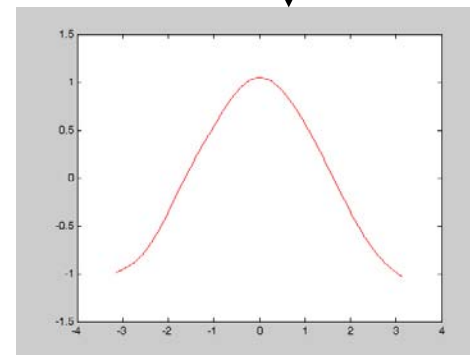
# Example



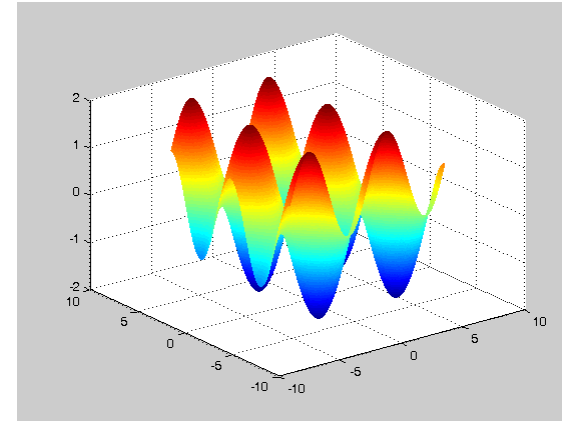
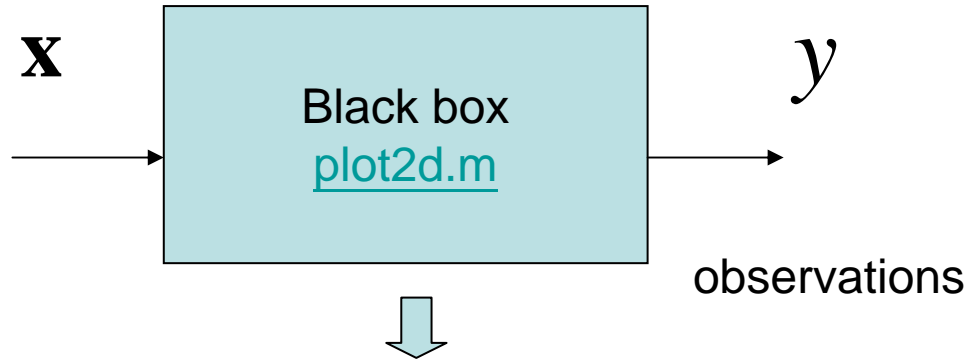
Create paired data  
[sampling.m](#)



**DDFA**  
[learning.m](#)

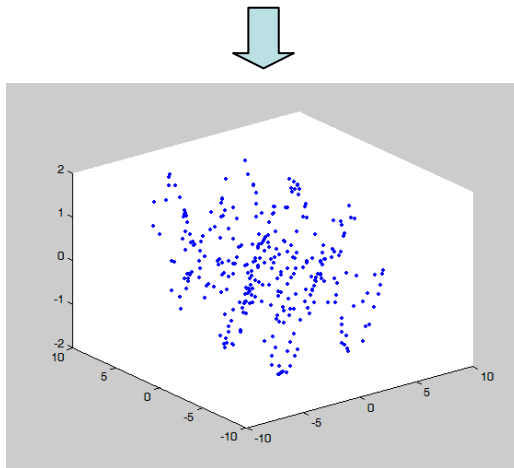


# Example



$$y = \cos(x_1) + \sin(x_2)$$

↓  
Create paired data  
[sampling2.m](#)



```
M=input\('M:'\);  
\[a,b,r\]=learn\_MLP\(x',y',M\);
```

↓  
[E=mean\\_square\\_error2\(x,y,a,b,r\)](#)

# Mean Square Error

$$E(r, a, b) = \frac{1}{n} \sum_{i=1}^n (y_i - f(\mathbf{x}_i; r, a, b))^2$$



# Mean square error

- Head:  $E = \text{mean\_square\_error2}(x, y, a, b, r)$

- Body:

$E = 0$

$n = \text{size}(x, 2)$

for  $i=1:n$

a)  $x_i = x(:, i)$

b)  $y_i = \text{eval\_MLP2}(x_i, r, a, b)$

c)  $e_i = y_i - y(i)$

d) Add the square of  $e_i$  to  $E$

$E = E/n$

# DDFA

[demo\\_fa2d.m](#)

[fa1d.m](#)