



## Neural Network Functions

May 11, 2026

This will be Tutorial 180 of the serie maXbox Starters.

Today we take a look at various functions from the topic of Neural Networks. The best Delphi functions to explain a neural network are the ones that map directly to the model's steps: **initialize**, **forward pass**, **activation**, **loss**, **backpropagation**, and **weight update**. In Delphi, it's usually clearest to organize these as small procedures/functions rather than one big routine, and Delphi ANN examples and FANN bindings follow that same structure like also Keras4Delphi. ibrtses+2

```

692  '{"x1": 364, "y1": 26, "x2": 400, "y2": 42}}, {"text": "Quietest", "bounding_box": {"x1": 406, '+
693  "'y1": 26, "x2": 485, "y2": 45}}, {"text": "Moments...", "bounding_box": {"x1": 490, "y1": 26, '+
694  "'x2": 599, "y2": 42}}]";
695
696  const testRawJSONStringObject =
697  [
698    {label: 'dining table', confidence: 0.63, bounding_box: {x1: 122, y1: 308, x2:
699    604, y2: 679}}, {label: 'bench', confidence: 0.57, bounding_box: {x1: 122, y1:
700    308, x2: 604, y2: 679}}, {label: 'bench', confidence: 0.41, bounding_box: {x1:
701    93, y1: 119, x2: 615, y2: 665}}, {label: 'dining table', confidence:
702    0.37, bounding_box: {x1: 92, y1: 115, x2: 617, y2: 667}}, {label:
703    'bed', confidence: 0.35, bounding_box: {x1: 98, y1: 173, x2: 617, y2:
704    670}}, {label: 'bench', confidence: 0.32, bounding_box: {x1: 316, y1:
705    537, x2: 521, y2: 671}}, {label: 'chair', confidence: 0.3, bounding_box:
706    {x1: 149, y1: 339, x2: 583, y2: 673}}]
707
const

```

3.14.3 (tags/v3.14.3:323c59a, Feb 3 2026, 16:04:56) [MSC v.1944 64 bit (AMD64)]  
[{'label': 'dining table', 'confidence': '0.63', 'bounding\_box': {'x1': '122', 'y1': '308', 'x2': '604', 'y2': '679'}},  
{'label': 'bench', 'confidence': '0.57', 'bounding\_box': {'x1': '122', 'y1': '308', 'x2': '604', 'y2': '679'}}, {'label':  
'bench', 'confidence': '0.41', 'bounding\_box': {'x1': '93', 'y1': '119', 'x2': '615', 'y2': '665'}}, {'label': 'dining table',  
'confidence': '0.37', 'bounding\_box': {'x1': '92', 'y1': '115', 'x2': '617', 'y2': '667'}}, {'label': 'bed', 'confidence':  
'0.35', 'bounding\_box': {'x1': '98', 'y1': '173', 'x2': '617', 'y2': '670'}}, {'label': 'bench', 'confidence': '0.32',  
'bounding\_box': {'x1': '316', 'y1': '537', 'x2': '521', 'y2': '671'}}, {'label': 'chair', 'confidence': '0.3',  
'bounding\_box': {'x1': '149', 'y1': '339', 'x2': '583', 'y2': '673'}}]

## Good function set

- **InitializeNetwork** — creates layers, weights, and biases.
- **ForwardPass** — computes outputs from inputs.
- **ActivateNeuron** — applies sigmoid, tanh, ReLU, etc.
- **ComputeLoss** — compares predicted vs target output.
- **Backpropagate** — computes error gradients.
- **UpdateWeights** — applies learning rate and weight changes.
- **TrainEpoch** — runs one full training pass over the dataset.
- **Predict** — returns the network output for new inputs.  
blogs.embarcadero+2

## Why these are the best

These names make the neural network easy to explain because each function matches a conceptual stage in the math. That is also how Delphi ANN examples and wrapper libraries tend to split the work: network creation, training, running, and saving/loading.  
github+2

## Simple Delphi skeleton

```

delphifunction ActivateNeuron(X: Double): Double;
begin

```

```
    Result:= 1 / (1 + Exp(-X)); // sigmoid
end;

function ForwardPass(const Inputs: TArray<Double>):
TArray<Double>;
begin
    { compute weighted sums, then activate }
end;

function ComputeLoss(const Output, Target: TArray<Double>):
Double;
begin
    { measure error }
end;

procedure Backpropagate;
begin
    { compute gradients }
end;

procedure UpdateWeights;
begin
    { apply learning rate }
end;
```

### **If you want it teachable**

For explaining the concept, I would present the functions in this order:

1. InitializeNetwork
2. ForwardPass
3. ActivateNeuron
4. ComputeLoss
5. Backpropagate
6. UpdateWeights
7. TrainEpoch
8. Predict

## 9. [ibrtses+1](#)

### Delphi-specific tip

If your goal is to **teach** rather than optimize, keep the code explicit: use arrays, loops, and separate helper functions for dot products, activations, and gradient steps. Delphi ANN examples and FANN wrappers show that this modular style is practical and easy to extend.[stackoverflow+2](#)

A compact teaching version could be built around just three core procedures: **ForwardPass**, **Backpropagate**, and **UpdateWeights**, with helper functions for activation and loss.

## Install Keras4Delphi

Keras4Delphi is installed like a Delphi library component: download the source, add the package or source paths to Delphi, and install the design-time package if the project provides one. The project README also notes that you must install **keras**, **numpy**, and a backend such as TensorFlow, CNTK, or Theano on the Python side that Keras depends on.[keras+1](#)

### Typical setup

1. Clone or download the Keras4Delphi source from the project [repository.github](#)
2. Add the library source path in Delphi so the units are found by the compiler.[stackoverflow](#)
3. Open the runtime package and compile it.[stackoverflow](#)
4. Open the design-time package and install it into the IDE if the project includes one.[stackoverflow](#)
5. Make sure Python-side dependencies are installed: **keras**, **numpy**, and a supported backend.[keras+1](#)

### Delphi side

If the package includes **.dpk** files, the usual Delphi workflow is compile the runtime package first, then install the design-time package. That is the standard Delphi component-install pattern, not something special to Keras4Delphi.[stackoverflow](#)

A minimal source-path setup usually looks like this:

- Add the Keras4Delphi source folder to **Tools > Options > Language > Delphi > Library**.
- Add any required subfolders if units are split by feature or backend.
- Rebuild the package after changing paths.github+1

### Python side

Keras itself is a Python library, so Keras4Delphi depends on a working Python environment. Keras' current documentation says you install Keras via **pip**, and you also need a backend such as TensorFlow, JAX, or PyTorch depending on the Keras version you are using. [keras](#)

For older Keras4Delphi projects, the repository specifically mentions installing **keras**, **numpy**, and a backend such as TensorFlow, CNTK, or Theano.[github](#)

### Common problems

- Delphi cannot find units: the library path is missing or the package source folder is not on the search path.[stackoverflow](#)
- Package compiles but IDE install fails: compile the runtime package first, then the design-time package.[stackoverflow](#)
- Keras calls fail at runtime: the Python environment is missing Keras, NumPy, or the backend framework.keras+1

The quickest path is usually: install Python dependencies first, then add Keras4Delphi source paths in Delphi, compile the runtime package, and finally install the design-time package if available. By the way also the Delphi 13.1 patch is on its way:

11:21



**RAD Studio 13.1 May Patch**

11:28



#### [Quality Portal issues addressed](#)

The following publicly reported Quality Portal issues are addressed by this patch:

- RSS-5314 Assert and AssertErrorProc broken in Delphi 13.1

## Readme

May 5, 2026

The RAD Studio 13.1 May Patch delivers a set of quality improvements to the 13.1 release. It primarily resolves issues in the Delphi Arm64EC toolchain and adds support for the latest Apple SDKs for macOS and iOS. The patch also addresses a problem with AssertErrorProc and an issue in the C++ Formatter.

Installing this patch is highly recommended for all RAD Studio 13.1, Delphi 13.1, and C++Builder 13.1 customers.

### Installation via GetIt

If you download the patch via GetIt, it is installed automatically and a backup of the replaced files is created. Note that the actual download (approximately 200MB) occurs while the patch is running in a console window. This operation may take some time, depending on your connection speed.

Note: The patch includes an updated version of PAServer for macOS and iOS. This is copied to the patch download folder. You must manually

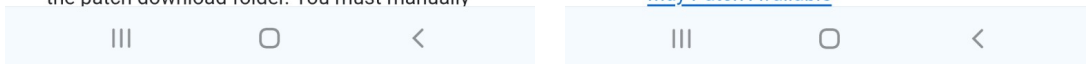
- RSS-5218 No soapserver.dcp release file in the RAD Studio Professional installation
- RSS-5193 Skia apps for Ubuntu crash on startup
- RSS-5190 Trying to compile a simple FMX Mac Arm64 app using XCode 26.4 and 26.4 SDK fails with "...does not contain arm64 architecture.."
- RSS-5163 "[DCC Fehler] E2597 Id: file too small (length=0) for architecture arm64" when compiling with iPhoneOS 26.4 SDK
- RSS-5153 RAD Studio 13.1 C++ Formatter crashes in compclangformat.dll when a user clang-format file is present

Additional Delphi Arm64EC-related fixes include:

- Proper handling of AV exceptions when invoking code via RTTI
- Fixes for issues invoking platform APIs after calling functions in an ARM64EC DLL
- Improvements to localization support

### Links

- 2026.05.05 [Reddit Post](#) [RAD Studio 13.1 May Patch Available](#)



RAD 13.1 Patch

The first Keras4Delphi neural-network example is essentially: use Python4Delphi/Keras4Delphi to run a simple Keras model in a Delphi GUI (usually `Sequential` with one or two `Dense` layers) on dummy or small data, then call `fit` and `predict` from Delphi-hosted Python code.

Below is a practical "Hello-World"-style example you can drop into a Delphi project that already has Keras4Delphi/Python4Delphi wired up.

1. Python script (run inside Delphi via P4D / Keras4Delphi)

```

1 | # Python script (run in the Python4Delphi Memo / Executor)
2 | import numpy as np
3 | from keras.models import Sequential
4 | from keras.layers import Dense
5 |
6 | # 1. Generate dummy data
7 | N = 1000
8 | DIM = 4
9 |
10 | X_train = np.random.random((N, DIM))
11 | y_train = np.random.randint(2, size=(N, 1))

```

```
12
13 X_test = np.random.random((100, DIM))
14 y_test = np.random.randint(2, size=(100, 1))
15
16 # 2. Build model
17 model = Sequential()
18 model.add(Dense(10, activation='relu', input_dim=DIM))
19 model.add(Dense(1, activation='sigmoid'))
20
21 # 3. Compile
22 model.compile(
23     optimizer='adam',
24     loss='binary_crossentropy',
25     metrics=['accuracy']
26 )
27
28 # 4. Train
29 model.fit(X_train, y_train, epochs=10, batch_size=32, verbose=0)
30
31 # 5. Test
32 loss, acc = model.evaluate(X_test, y_test, verbose=0)
33 print("Test loss: {:.4f}".format(loss))
34 print("Test accuracy: {:.2f}%".format(acc * 100))
```

This pattern is the standard “first neural network in Keras” and is exactly what demos with Python4Delphi-style toolkits adopt for Keras4Delphi-like scenarios. It Teaches:

Evaluation: `model.evaluate`.

Network creation: `Sequential` + `Dense` layers.

Loss and optimizer choice: `binary_crossentropy` + `adam`.

Training loop: `model.fit`.

## Debug common Keras4Delphi execution errors

Common Keras4Delphi errors usually come from Python-side problems (missing modules, GPU / CUDA issues, or bad shapes), or Delphi-side wiring (bad Python4Delphi calls, bad strings, or threading). Because Keras4Delphi is just a Delphi wrapper around Keras running in Python, you debug the Python code and the interop layer separately.`keras+1`

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# 1. Typical Keras4Delphi errors

## A) Python-import / environment errors

- **ModuleNotFoundError**: No module named 'keras' or 'tensorflow'  
→ Python env is missing Keras or backend.
- **Seg-fault** or **CUDA init failure** when training  
→ GPU drivers, CUDA, or TensorFlow config is wrong.
- **ValueError** or **InvalidArgumentError** about array shape  
→ X/Y arrays from Delphi do not match model input/output dimensions.delhipraxis+1

## B) Delphi-side errors

- **Crash** or **Access violation** when calling **ExecString**  
→ Bad string encoding, unterminated string, or invalid Python code passed.
- **No output** or **silent failure**  
→ Python4Delphi **Memo / Output** redirection is not hooked, or **ExecString** fails silently.
- **Hanging** on **ExecScript**  
→ Infinite loop or misconfigured Python (e.g., **print** flood, interactive **input**, or long-running **fit** without worker threads).delhipraxis+1

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## 2. Debugging strategy

### 1. Confirm Python side works standalone

Run the exact same Keras code in `python.exe` (or a Jupyter/IDE) on the same machine, with the same virtual environment that Keras4Delphi uses. If it fails there, fix the Keras environment before touching Delphi.github+1

### 2. Make sure imports are visible

Before any Keras code, insert minimal checks:

```
pythonimport sys
```

```
print(sys.path)

import keras
print("Keras version:", keras.__version__)

import tensorflow
print("TensorFlow version:", tensorflow.__version__)
```

Capture that output in the Delphi TMemo or PythonOutput. If `import keras` fails, the Keras installation or Python path is wrong.[github+1](#)

### 3. Check shapes and data types

Common Keras error:

```
pythonValueError: The last dimension of the inputs to Dense
should be defined.
```

Means input shape is not fully specified. Add print-checks in Python:

```
pythonprint("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
```

Make sure what you pass from Delphi matches the model's `input_shape`.[github+1](#)

### 4. Wrap Keras calls in try-except

```
pythonimport traceback

try:
    model = ...
    model.compile(...)
    model.fit(X_train, y_train, ...)
except Exception as e:
    print("Exception:", str(e))
    traceback.print_exc()
```

Pipe that output back to Delphi so you see the full Keras traceback instead of just a crash.keras+1

### 5. Delphi-side protections

- Use a helper function that prints from Python into a Delphi Memo:

```
delphiprocedure TForm1.RunPythonScript(const Code: string);
begin
    PythonEngine1.IO := PythonGUIInputOutput1;    // show output
in a Memo
    PythonEngine1.ExecString(PWideChar(Code));
end;
```

- Do not call long-running `model.fit` in the main UI thread; use a background thread or `TTask` so the form does not freeze.delhipraxis+1

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## 3. Example debug routine

If Keras4Delphi “just crashes”, add a minimal diagnosis routine:

```
pythonimport sys
import platform

print("Python executable:", sys.executable)
print("Python version:", platform.python_version())

try:
    import keras
    print("Keras imported OK")
except Exception as e:
    print("Keras import error:", e)
    import traceback
    traceback.print_exc()
```

Call this first from Delphi. If this already fails, the rest will fail; the problem is Python-setup, not Keras-model-code.github+1

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## 4. Quick checklist

- Keras4Delphi is configured to use the right Python interpreter (same one where `python -c "import keras"` works).[keras+1](#)
- X/Y tensors passed from Delphi to Python have correct shape and `np.float32` type.[github+1](#)
- Long `model.fit` runs in a background thread; UI is not blocked.[pythongui+1](#)
- All errors are printed in Python with `traceback`, and captured in Delphi's output.[github+1](#)

If you paste a specific error message or stack trace (Delphi AV or Python exception), I can narrow it down to the exact Keras4Delphi wiring or model bug.

## Conclusion

### Key functions to show

Use these as your "teaching functions":

#### 1. CreateNetwork / InitializeNetwork

- Sets number of layers, neurons per layer, and initializes random weights and biases.
- This is the **network structure** step.

#### 2. ForwardPass / CalculateOutputs

- Performs a full forward pass from input layer to output layer using weights and an activation function (e.g., sigmoid, tanh, ReLU).
- Demonstrates how the model **transforms input → prediction**.

#### 3. ActivateNeuron / ApplyActivation

- Applies a single activation function to a neuron's weighted sum.
- You can show **Sigmoid, Tanh, or ReLU** side by side.

#### 4. ComputeLoss / ComputeError

- Computes the difference between desired output and network output, often mean squared error or cross-entropy.
- This is the **feedback signal** that drives learning.

#### 5. Backpropagate

- Propagates error backward and computes gradients for weights and biases.

- In pure-Pascal nets this is often implemented as `BackPropagateOneNode`-style loops, which is very instructive to walk through.

#### 6. `UpdateWeights / AdjustWeights`

- Applies gradients scaled by a learning rate to the weights and biases.
- Shows how the network learns from error.

#### 7. `TrainEpoch / TrainNetwork`

- Runs one pass over all training samples, calling `ForwardPass` → `ComputeLoss` → `Backpropagate` → `UpdateWeights`.
- This is the outer training loop.

#### 8. `Predict / RunNetwork`

- Runs `ForwardPass` without training, and returns the output.
- Shows inference vs training.

```
1 //Minimal Delphi teaching skeleton
2 type
3   TNeuralNet = class
4   public
5     procedure CreateNetwork(NumInputs, NumHidden, NumOutput
6     procedure ForwardPass(Inputs: array of Single; var Output: array of Single);
7     function ActivateNeuron(X: Single): Single; // e.g., sigmoid
8     procedure ComputeLoss(Target, Output: array of Single);
9     procedure Backpropagate;
10    procedure UpdateWeights(LearningRate: Single);
11    procedure TrainEpoch(Data: array of TSample);
12    procedure Predict(Input: array of Single; var Output: array of Single);
13  end;
```

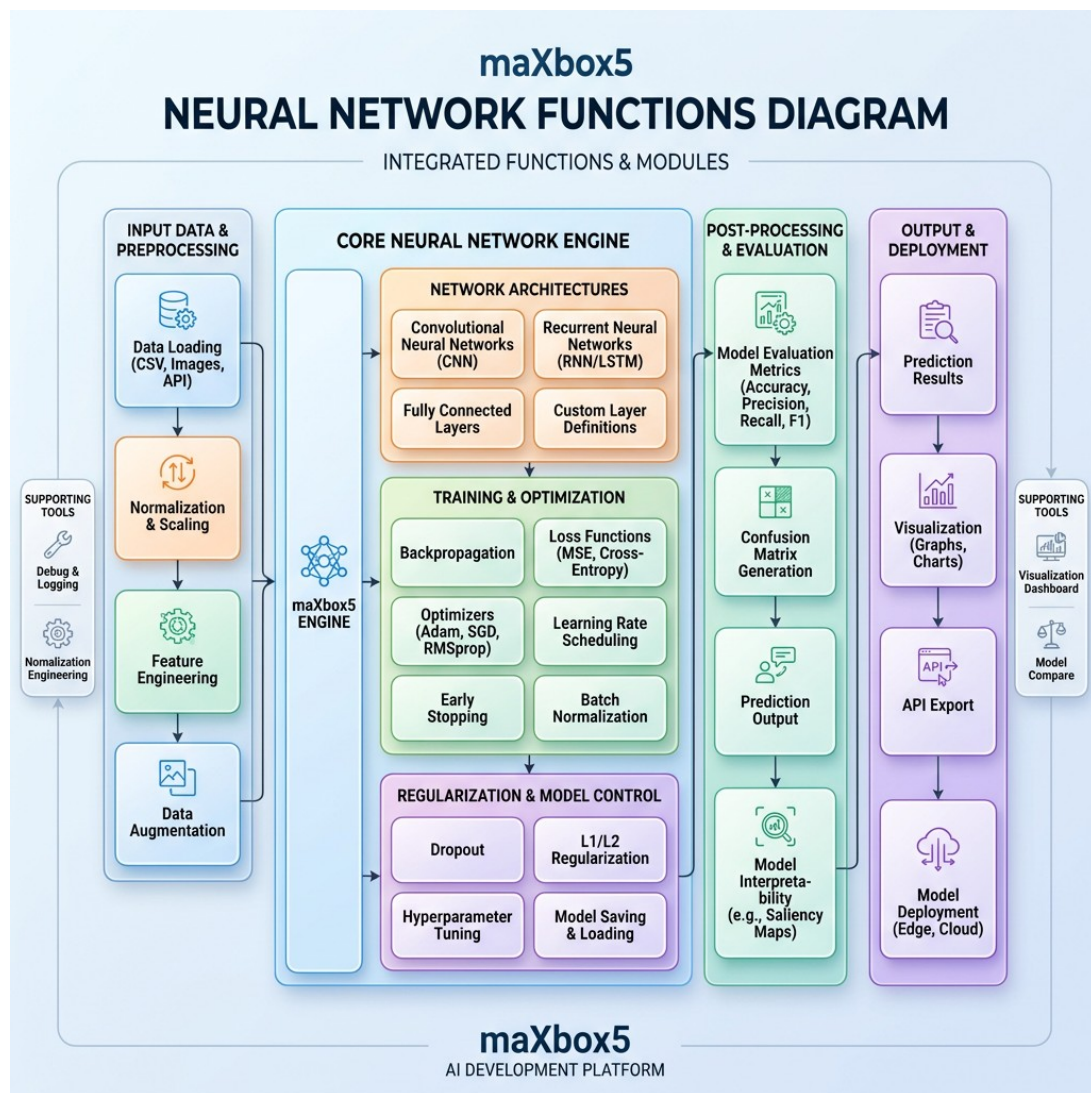


Diagram showing the integrated functions and modules of a neural network system with Python4Delphi.

```

1 // Simple network structure
2 type
3   TBackPropNet = class
4   private
5     FInputs:      array[0..1] of Single;
6     FHidden:      array[0..1] of Single;
7     FOutputs:     array[0..0] of Single;
8
9     FWeightsIH:   array[0..1, 0..1] of Single; // input t
10    FWeightsHO:   array[0..1, 0..0] of Single; // hidden
11
12    FHiddenErrors: array[0..1] of Single;
13    FOutputErrors: array[0..0] of Single;
14
15    FInputCount:  Integer;
16    FHiddenCount: Integer;
17    FOutputCount: Integer;
18    FRate:        Single;
19
20    procedure RandomizeWeights;
21    function Sigmoid(X: Single): Single;
22    function SigmoidDeriv(X: Single): Single;

```

```

23
24     public
25         constructor Create(InCnt, HidCnt, OutCnt: Integer; Lear
26
27         procedure Forward;
28         procedure Backward(const Target: array of Single);
29         procedure Train(MinError: Single; MaxEpochs: Integer);
30     end;

```

### Complete Console Code Example (CCCE)

Here is a self-contained Delphi console-style example that solves the XOR problem with a simple backpropagation neural network, written in pure Pascal (no external libraries). It uses a 2-input → 2-hidden → 1-output layout with **sigmoid** activations and standard backpropagation for weight updates.

#### 1. Complete Delphi executable (uses System.SysUtils)

```

1     program XORBackprop;
2
3     {$APPTYPE CONSOLE}
4
5     uses
6         System.SysUtils;
7
8     type
9         TBackPropNet = class
10        private
11            FInputs:         array[0..1] of Single;
12            FHidden:         array[0..1] of Single;
13            FOutputs:        array[0..0] of Single;
14
15            FWeightsIH:      array[0..1, 0..1] of Single; // input
16            FWeightsHO:      array[0..1, 0..0] of Single; // hidden
17
18            FHiddenErrors:   array[0..1] of Single;
19            FOutputErrors:   array[0..0] of Single;
20            FRate:           Single;
21
22            function Sigmoid(X: Single): Single;
23            function SigmoidDeriv(X: Single): Single;
24            procedure RandomizeWeights;
25
26        public
27            constructor Create(LearnRate: Single);
28            procedure Forward;
29            procedure Backward(const Target: Single);
30            function TrainXOR(Epochs: Integer; MinError: Single):
31            function TestXOR(Input0, Input1: Single): Single;
32        end;

```

```
33
34 constructor TBackPropNet.Create(LearnRate: Single);
35 begin
36     FRate := LearnRate;
37     RandomizeWeights;
38 end;
39
40 function TBackPropNet.Sigmoid(X: Single): Single;
41 begin
42     Result := 1 / (1 + Exp(-X));
43 end;
44
45 function TBackPropNet.SigmoidDeriv(X: Single): Single;
46 begin
47     Result := X * (1 - X);
48 end;
49
50 procedure TBackPropNet.RandomizeWeights;
51 var
52     i, j: Integer;
53 begin
54     for i := 0 to 1 do
55         for j := 0 to 1 do
56             FWeightsIH[i, j] := (Random - 0.5) * 2;
57
58         for i := 0 to 1 do
59             for j := 0 to 0 do
60                 FWeightsHO[i, j] := (Random - 0.5) * 2;
61 end;
62
63 procedure TBackPropNet.Forward;
64 var
65     i, j: Integer;
66     Sum: Single;
67 begin
68     // Hidden layer
69     for j := 0 to 1 do begin
70         Sum := 0;
71         for i := 0 to 1 do
72             Sum := Sum + FInputs[i] * FWeightsIH[i, j];
73         FHidden[j] := Sigmoid(Sum);
74     end;
75
76     // Output layer
77     for j := 0 to 0 do begin
78         Sum := 0;
79         for i := 0 to 1 do
80             Sum := Sum + FHidden[i] * FWeightsHO[i, j];
81         FOutputs[j] := Sigmoid(Sum);
82     end;
83 end;
84
85 procedure TBackPropNet.Backward(const Target: Single);
86 var
87     i, j: Integer;
88     Sum: Single;
89 begin
90     // Output error
```

```

91     FOutputErrors[0] := (Target - FOutputs[0]) * SigmoidDeri
92
93     // Hidden errors
94     for j := 0 to 1 do begin
95         Sum := 0;
96         for i := 0 to 0 do
97             Sum := Sum + FOutputErrors[i] * FWeightsHO[j, i];
98         FHiddenErrors[j] := Sum * SigmoidDeriv(FHidden[j]);
99     end;
100
101     // Update hidden → output
102     for i := 0 to 1 do
103         for j := 0 to 0 do
104             FWeightsHO[i, j] :=
105                 FWeightsHO[i, j] + FRate * FHidden[i] * FOutputErr
106
107     // Update input → hidden
108     for i := 0 to 1 do
109         for j := 0 to 1 do
110             FWeightsIH[i, j] :=
111                 FWeightsIH[i, j] + FRate * FInputs[i] * FHiddenErr
112     end;
113
114     function TBackPropNet.TrainXOR(Epochs:Integer; MinError: S
115     var
116         Epoch, Pattern: Integer;
117         Input0, Input1, Target, TotalError: Single;
118     begin
119         Result := False;
120         for Epoch := 1 to Epochs do begin
121             TotalError := 0;
122
123             // XOR training set
124             for Pattern := 0 to 3 do begin
125                 Input0 := Pattern and 1;
126                 Input1 := (Pattern shr 1) and 1;
127                 Target := (Input0 + Input1) mod 2; //0 xor 0 = 0; 1
128                 FInputs[0] := Input0;
129                 FInputs[1] := Input1;
130
131                 Forward;
132                 Backward(Target);
133                 TotalError := TotalError + Sqr(Target - FOutputs[0])
134             end;
135
136             TotalError := Sqrt(TotalError);
137             if TotalError < MinError then begin
138                 WriteLn('XOR converged after ', Epoch, ' epochs(error: '
139                 Result := True;
140                 Exit;
141             end;
142
143             if Epoch mod 1000 = 0 then
144                 WriteLn('Epoch ', Epoch, ', Error: ', TotalError:0:6
145         end;
146     end;
147
148     function TBackPropNet.TestXOR(Input0, Input1: Single): Sir

```

```
149 begin
150     FInputs[0] := Input0;
151     FInputs[1] := Input1;
152     Forward;
153     Result := FOutputs[0];
154 end;
155
156 var Net: TBackPropNet;
157     Ans: Single;
158 begin
159     Randomize;
160     Net := TBackPropNet.Create(1.0);
161
162     if not Net.TrainXOR(10000, 0.01) then
163         WriteLn('XOR training did not converge.');
```

164

```
165     WriteLn(#10, 'XOR solution:');
166     Ans := Net.TestXOR(0, 0); WriteLn('0 xor 0 = ', Ans:0:6)
167     Ans := Net.TestXOR(0, 1); WriteLn('0 xor 1 = ', Ans:0:6)
168     Ans := Net.TestXOR(1, 0); WriteLn('1 xor 0 = ', Ans:0:6)
169     Ans := Net.TestXOR(1, 1); WriteLn('1 xor 1 = ', Ans:0:6)
170
171     ReadLn;
172 end.
```

### What this example shows

- A 4-pattern XOR set  $((0,0) \rightarrow 0, (0,1) \rightarrow 1, (1,0) \rightarrow 1, (1,1) \rightarrow 0)$ .
- A small 2-2-1 network with **sigmoid** activations and backpropagation.
- Training loop that stops early when error drops below **0.01**.

```

528 Randomize;
529 //Net := TBackPropNet.Create(1.0);
530 TBackPropNetCreate(1.7)
531
532 processmessagesOFF;
533 if not TBackPropNetTrainXOR(12000, 0.01) then
534   WriteLn('XOR training did not converge. ');
535 processmessagesON;
536
537 WriteLn(#10+ 'XOR solution: ');
538 //Ans := Net.TestXOR(0, 0); WriteLn('0 xor 0 = ', Ans:0:6);
539 Ans:= TBackPropNetTestXOR(0, 0); WriteLn('0 xor 0 = '+flots(Ans));
540 Ans:= TBackPropNetTestXOR(0, 1); WriteLn('0 xor 1 = '+flots(Ans));
541 Ans:= TBackPropNetTestXOR(1, 0); WriteLn('1 xor 0 = '+flots(Ans));
542 Ans:= TBackPropNetTestXOR(1, 1); WriteLn('1 xor 1 = '+flots(Ans));

```

```

maXbox5 C:\maxbox\maxbox51\examples\1484_neural_network_functions.txt Ct:12/05/2026 20:18:43 Mem:62% Rtime:0:0:9.887 Thr:8 S
Epoch 7000, Error: 0.586495697498322
Epoch 8000, Error: 0.583211779594421
Epoch 9000, Error: 0.580429672194885
Epoch 10000, Error: 0.578028738498688
Epoch 11000, Error: 0.575924634933472
Epoch 12000, Error: 0.574058711528778
XOR training did not converge.
XOR solution:
0 xor 0 = 0.033851519227028
0 xor 1 = 0.875784456729889
1 xor 0 = 0.875794589519501
1 xor 1 = 0.541876196861267
mX5 executed: 12/05/2026 20:18:50 Runtime: 0:0:9.887 Memload: 62% use
RemObjects Pascal Script. Copyright (c) 2004-2026 by RemObjects Software & maXbox5

```

[https://sourceforge.net/projects/maxbox5/files/examples/1484\\_neural\\_network\\_functions.txt/download](https://sourceforge.net/projects/maxbox5/files/examples/1484_neural_network_functions.txt/download)

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## One response to “Neural Network Functions”



**Max Kleiner**

May 12, 2026

Cool Conclusion to remember

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