## Einführung in die Neuroinformatik

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## 1 Backpropagation [Pen and Paper]

1. Forwärts propagieren:

$$u_{1}^{(1)} = x_{1} \cdot w_{11}^{(1)} + x_{2} \cdot w_{21}^{(1)} + b_{1}^{(1)}$$

$$y_{1}^{(1)} = f_{1}(u_{1}^{(1)})$$

$$u_{1}^{(2)} = y_{1}^{(1)} \cdot w_{11}^{(2)} + y_{2}^{(1)} \cdot w_{21}^{(2)} + b_{1}^{(2)}$$

$$y_{1}^{(2)} = f_{2}(u_{1}^{(2)})$$

2. Fehler in der Ausgabeschicht bestimmen:

$$\delta_1^{(2)} = y_1^{(2)} - T_1$$

3. Backpropagation

$$\delta_1^{(1)} = \delta_1^{(2)} w_{11}^{(2)} f'\left(u_i^{(1)}\right)$$

4. Gewichte adaptieren

$$\tilde{w}_{11}^{(1)} = w_{11}^{(1)} + \eta x_1 \delta_1^{(1)}$$

## 2 Backpropagation [Matlab]

2.1

```
1 function [weights] = initWeights(inputDimensions, hiddenNeurons,
      output Dimensions)
2 %initWeights initializes the weights of the network
3 %
      Arguments:
4 %
          - input Dimensions: number of input neurons
5 %
          - hiddenNeurons: number of hidden neurons
  %
          - output Dimensyions: number of output neurons
  %
8 %
      Returns:
          - weights: struct with the parameters w1, w2, theta1 and
      theta2
  %
10
      rng(1337, 'combRecursive');
11
      weights.w1 = rand (hiddenNeurons, inputDimensions) - 0.5;
12
      weights.w2 = rand(outputDimensions, hiddenNeurons) - 0.5;
      weights.theta1 = rand(hiddenNeurons, 1) - 0.5;
14
      weights.theta2 = rand(outputDimensions, 1) - 0.5;
15
 end
  2.2
  function [y2, u2, y1, u1] = forward(inputX, weights, trans)
  %forward calculates the network output
3 %
      Arguments:
4 %
          - inputX: input data organized as samples x dimensions (
     each row denotes a point)
  %
          - weights: struct with the parameters w1, w2, theta1 and
      theta2
  %
          - trans: activation function f(x) of the hidden layer
6
  %
      u1 = weights.w1 * inputX + weights.theta1;
      v1 = trans(u1);
      u2 = weights.w2 * y1 + weights.theta2;
10
      y2 = u2;
12 end
  2.3
function [delta1, delta2] = propagateError(T, y2, w2, u1Diff)
2 %propagateError calculates the error of the network (delta1 and
     delta2)
з %
      Arguments:
4 %
          - T: teacher signal
5 %
          - y2: output of the last neuron
```

```
6 %
          - w2: weights matrix of the second layer
7 %
          - u1Diff: f'(u1)
  %
       delta2 = T-v2;
       delta1 = delta2 * (transpose(w2) .* u1Diff);
10
11
  end
  function y = transDiff(x)
      y = ones(size(x))./(cosh(x).^2);
  end
  2.4
  function [weights, errors] = train(hiddenNeurons, learnRate,
     inputX, outputT, epochs, trans, transDiff)
  %train trains the neural network
      Arguments:
  %
           - hiddenNeurons: number of hidden neurons
 %
          - learnRate: learning rate \eta
6 %
          - inputX: input data organized as samples x dimensions (
     each row denotes a point)
  %
          - outputT: teacher signal as column vector
  %
           - epochs: number of epochs to train the network
  %
          - trans: transfer function to use in the hidden layer (
      activation function)
  %
          - transDiff: derivative of the transfer function
10
11
  %
       assert (iscolumn (outputT), 'T must be a column vector');
12
       assert (size (inputX, 1) == size (outputT, 1), 'Each data point
1.3
           must have an associated label');
       rng(1337, 'combRecursive'); % For reproducibility (does also
14
           work with parfor: http://de.mathworks.com/help/distcomp
          /control-random-number-streams.html#btms9o )
       weights = initWeights(size(inputX,2), hiddenNeurons, size(
15
          outputT, 2));
       errors = zeros(epochs, 1);
16
       for e=1:epochs
           indexSet = randperm(size(inputX,1));
           for c=indexSet
20
               currentInput = transpose(inputX(c,:));
21
               trainerOutput = transpose(outputT(c,:));
22
               [mlpOutput, u2, hiddenOutput, u1] = forward(
                  currentInput , weights , trans );
```

```
[delta1, delta2] = propagateError(trainerOutput,
24
                   mlpOutput, weights.w2, transDiff(u1));
25
               weights.w1 = weights.w1 + learnRate * (delta1 *
26
                   transpose (currentInput));
                weights.w2 = weights.w2 + learnRate * delta2 *
27
                   transpose (hiddenOutput);
                weights.theta1 = weights.theta1 + learnRate * delta1
28
                weights.theta2 = weights.theta2 + learnRate * delta2
29
           end;
30
31
           [mlpOutput, u2, hiddenOutput, u1] = forward(transpose(
              inputX), weights, trans);
           diff = norm(mlpOutput-transpose(outputT))^2;
33
           errors(c) = diff;
34
       end;
  end
  2.5
1 % Initialization
2 % Generate data
s = 31;
[x, y, z] = peaks(s);
  data = [x(:) y(:) z(:)];
  X = data(:, 1:2);
  T = data(:, 3);
  eta = 0.01;
  [weights, E] = train (100, eta, X, T, 1000, @tanh, @transDiff);
1.0
11
  figure();
  subplot(2,2,1);
  surf(x,y,z);
  xlabel("x_1");
  ylabel("x 2");
  zlabel("peaks(x_1, x_2)");
   title ("Peaks-Funktion");
18
19
  subplot(2,2,2);
  output = forward (transpose (X), weights, @tanh);
  output = reshape(output, size(z));
```

```
surf(x,y,output);
    xlabel("x_1");
    ylabel("x_2");
    zlabel("f(x_1, x_2)");
    title ("Netz-Ausgabe");
28
29
    subplot(2,2,3);
    surf(x,y,abs(output-z));
    xlabel("x_1");
    ylabel("x_2");
33
    {\color{red}{\bf zlabel}} \, (\, {\color{red}{\tt "lpeaks}} \, (\, {\color{red}{\bf x\_1}} \, , \, \, \, {\color{red}{\bf x\_2}} \, ) \, \, - \, \, f \, (\, {\color{red}{\bf x\_1}} \, , {\color{red}{\bf x\_2}} \, ) \, \, | \, {\color{red}{\tt "lpeaks}} \, ) \, ;
    title ("Differenz der beiden Funktionen");
37
    subplot(2,2,4);
38
    plot (E);
39
  xlabel("i");
    ylabel("E(i)");
    title ("Fehlerverlauf");
43
   print("Plot.eps", "-depsc");
```

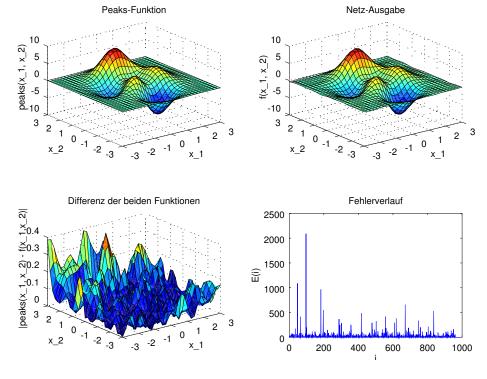


Abbildung 1: Ausgabe des Matlab-Skripts