COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

Training Neural Networks

CMSC 470

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Neural Networks so far

- Powerful non-linear models for classification

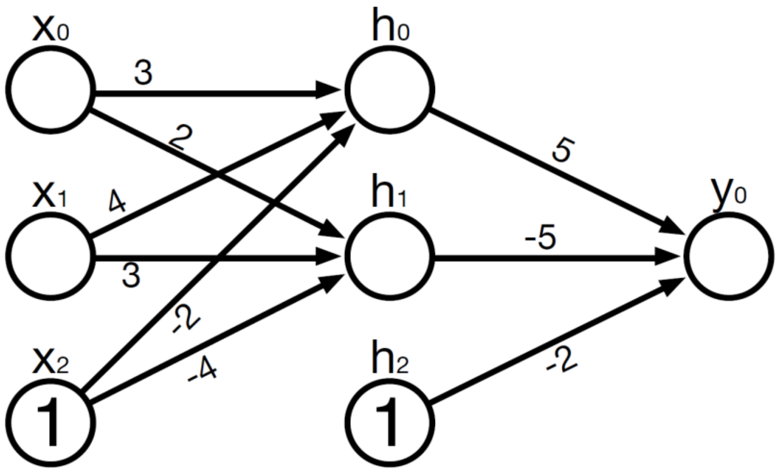
- Predictions are made as a sequence of simple operations
    - matrix-vector operations
    - non-linear activation functions

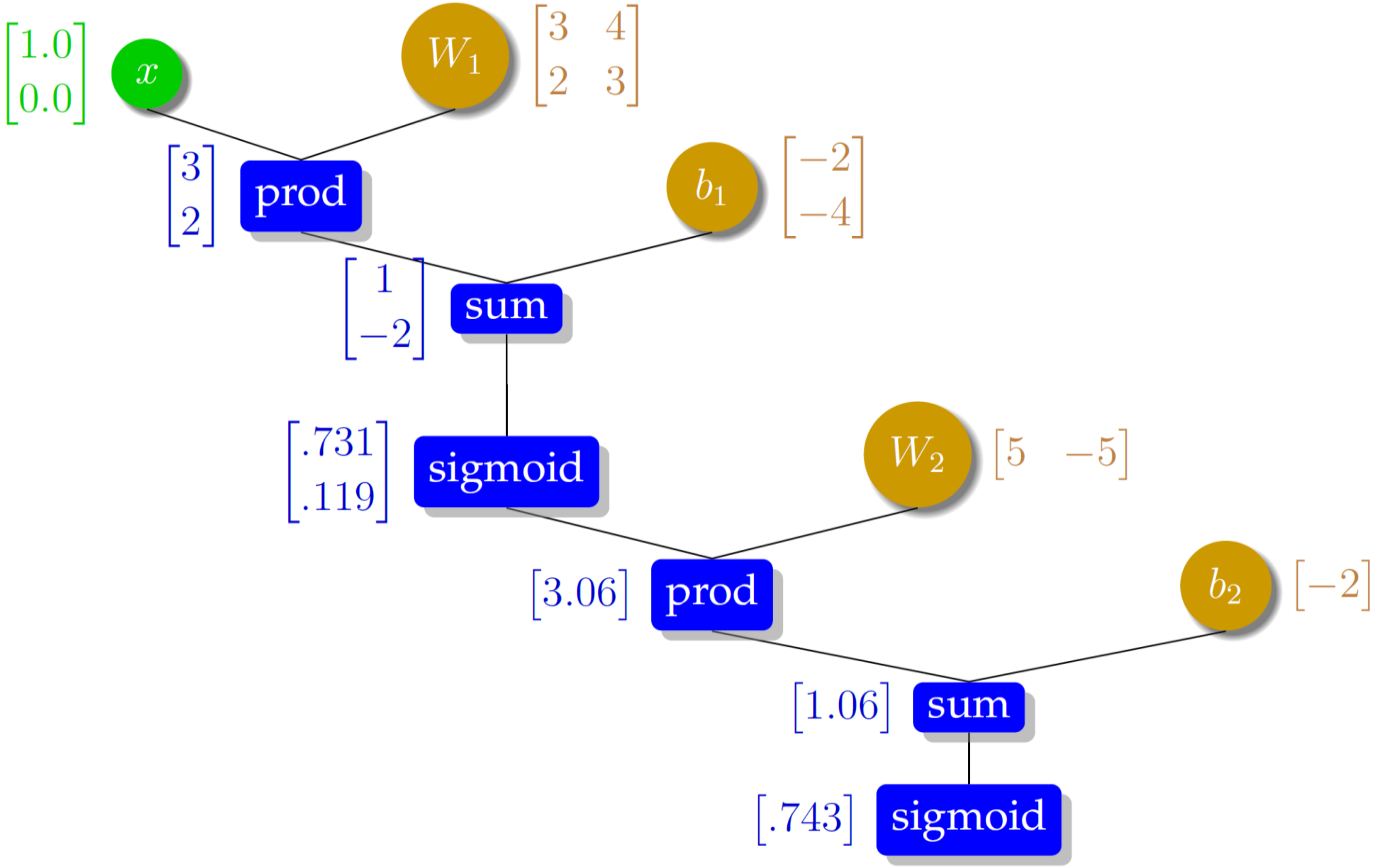
- Choices in network structure
    - Width and depth
    - Choice of activation function

- Feedforward networks
    - no loop

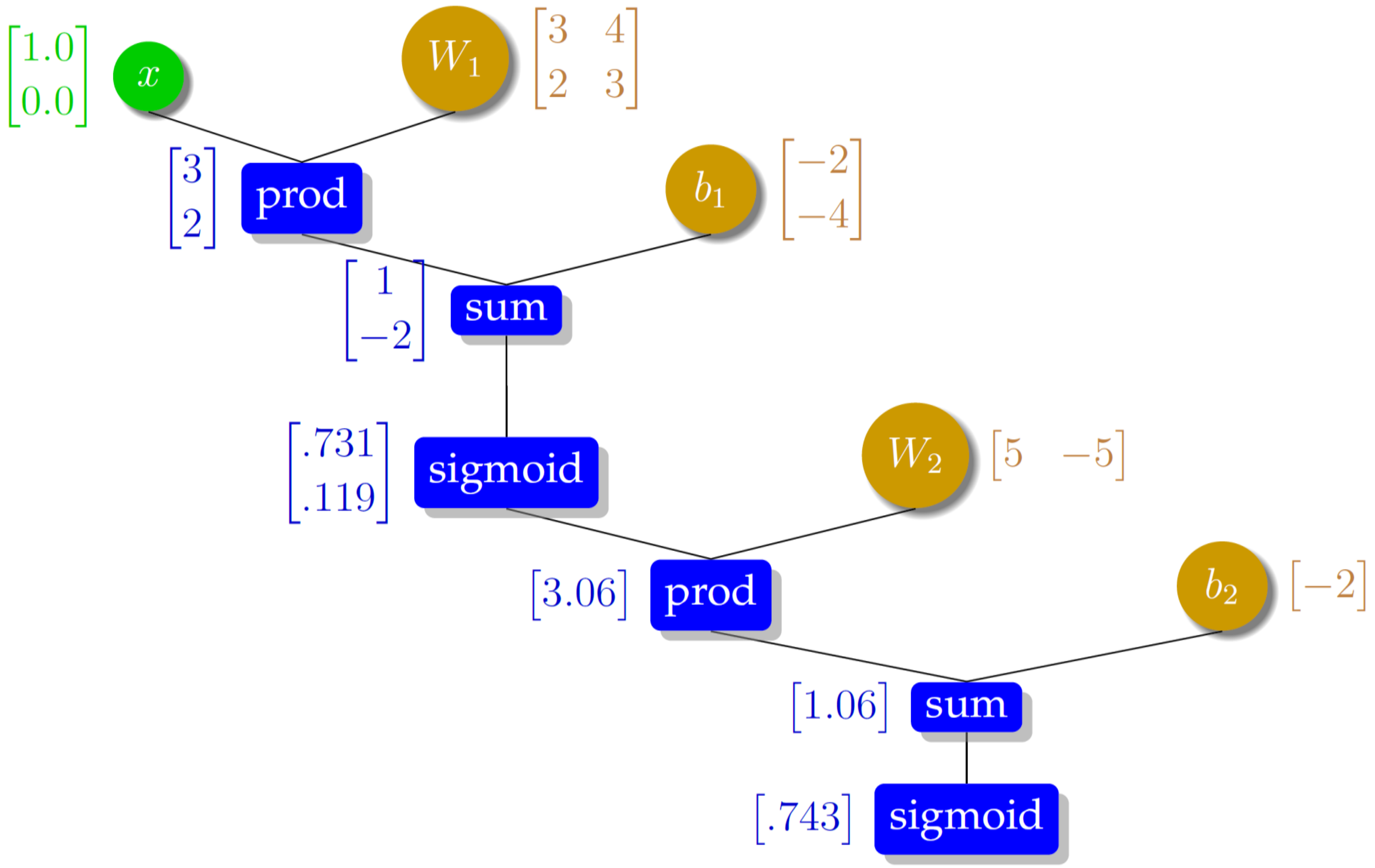
- Next: how to train

Neural Networks as Computation Graphs





Computation Graphs Make Prediction Easy: Forward Propagation consists in traversing graph in topological order



Computation Graph

- Graph contains 3 different types of nodes
  - Parameters of the models (e.g., W1, b1, W2, b2)
  - Input x
  - operations between parameters and input (e.g., product, sum, sigmoid)

- Acyclical directed graph
  - No recursion or loops

- So far each computation node in the graph should consist of
  - A function that executes its computation operation
  - Links to input nodes
  - When processing an example, the computed value

  (we'll add 2 more items to enable training)

How do we train a neural network?

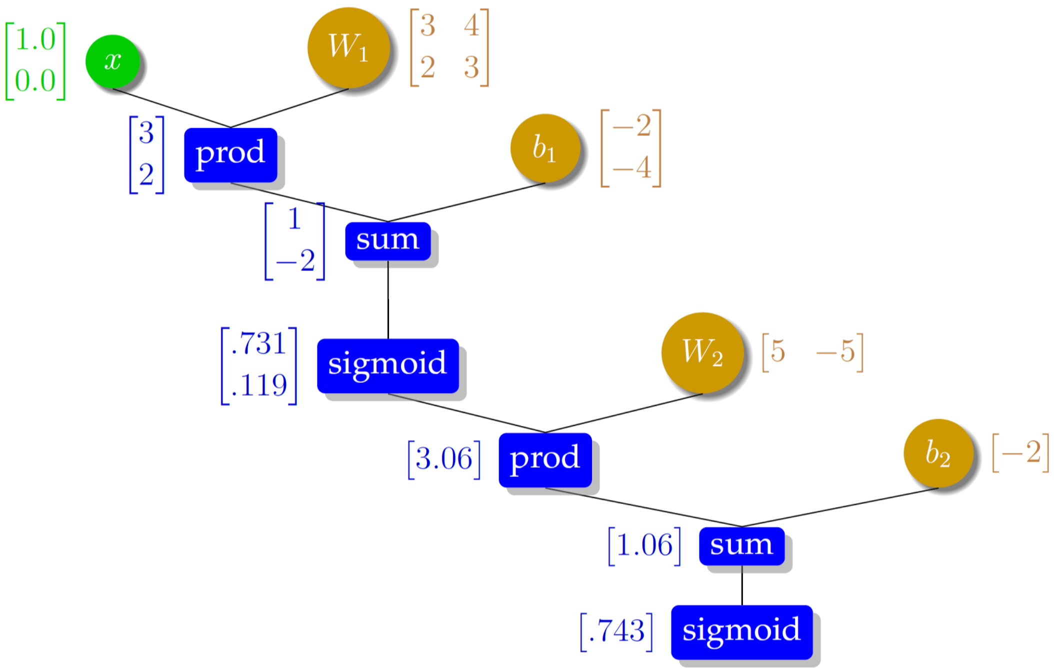
For training, we need

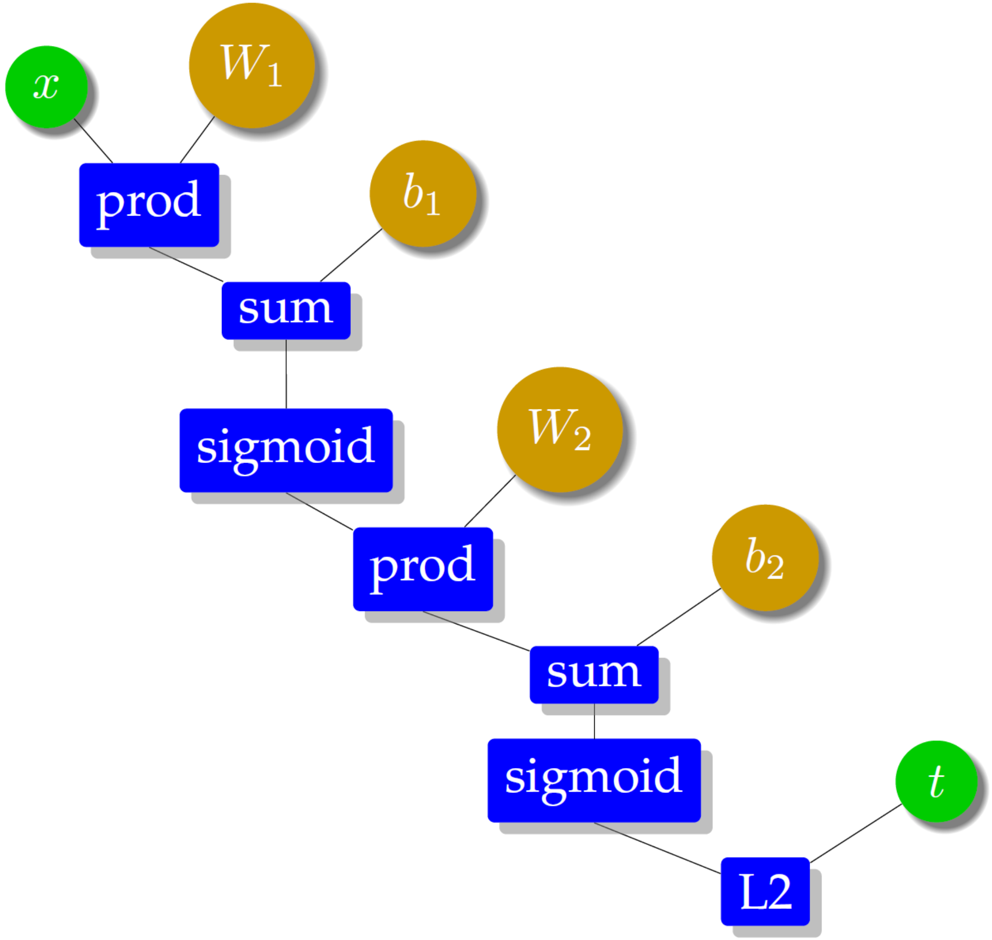
- Data: (a large number of) examples paired with their correct class (x,y)

- Loss/error function: quantify how bad our prediction y is compared to the truth t
  - E.g. squared error (aka L2 loss) $$\text{error} = \frac{1}{2}(t-y)^2$$

- An algorithm to minimize the loss: stochastic gradient descent

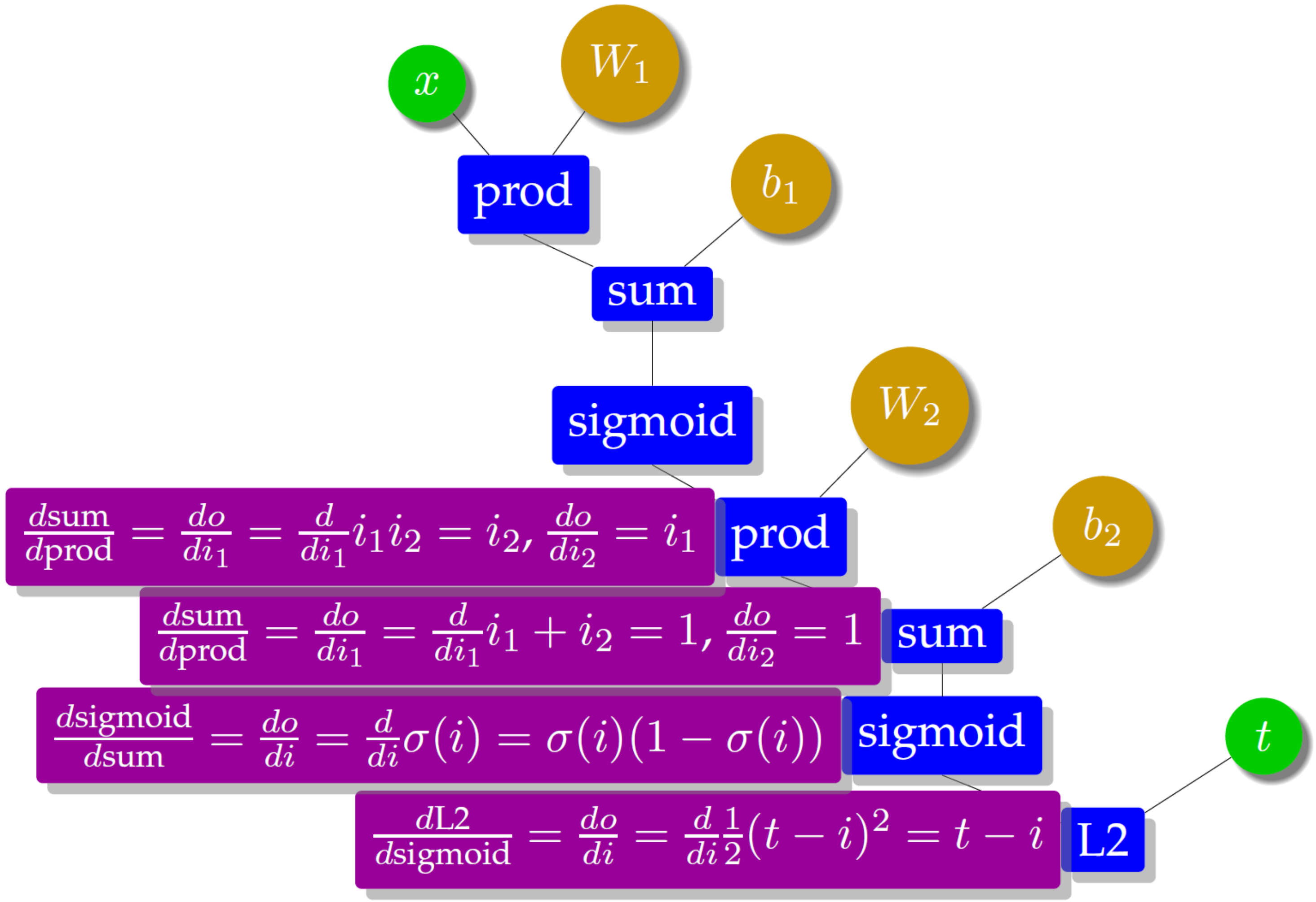
Extending the Computation Graph to Compute the Loss



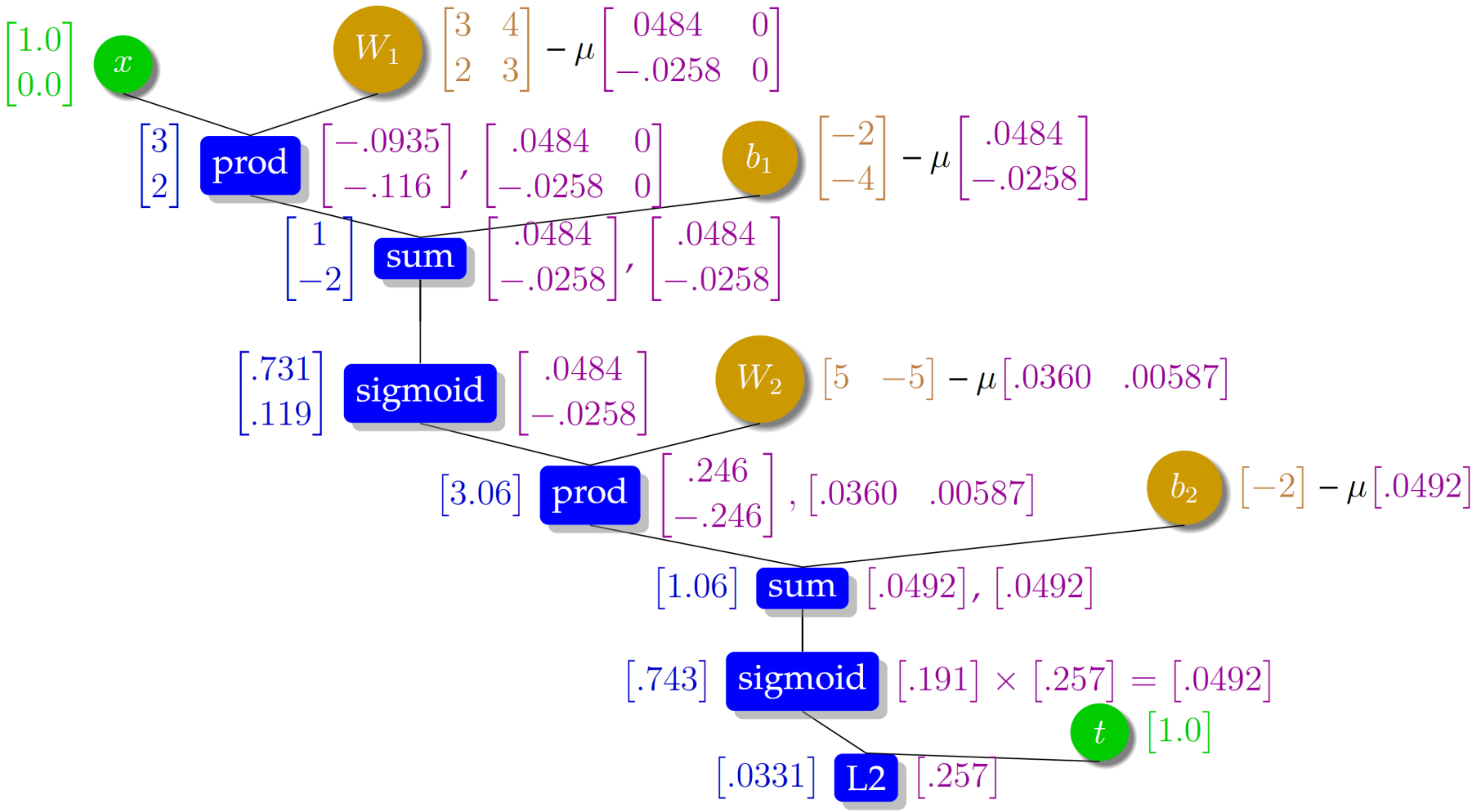


Computing Gradients: Chain rule decomposes computation of gradient along the nodes

$$\frac{dE}{dA} = \frac{dE}{dB}\frac{dB}{dA}$$



Training Illustrated



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- So far each computation node in the graph should consist of
  - A function that executes its computation operation
  - Links to input nodes
  - When processing an example in the forward pass, the computed value
  - **A function that executes its gradient computation**
  - **Links to children nodes (to obtain downstream gradient values)**
  - **When processing an example in the backward pass, the computed gradient**

Computation Graph: A Powerful Abstraction

- To build a system, we only need to:
  - Define network structure
  - Define loss
  - Provide data
  - (and set a few more hyperparameters to control training)

- Given network structure
  - Prediction is done by forward pass through graph (forward propagation)
  - Training is done by backward pass through graph (back propagation)
  - Based on simple matrix vector operations

- Forms the basis of neural network libraries
  - Tensorflow, Pytorch, mxnet, etc.

Exploiting parallel processing

- Using vector matrix operations helps
  - E.g., if a layer has 200 nodes a matrix operation Wh requires 200 x 200 = 40000 multiplications
  - Can benefit from efficient implementations for Graphics Processing Units (GPU)
- "Minibatch" training by processing multiple examples at a time helps further
  - Compute parameter updates based on a "minibatch" of examples
    - instead of one example at a time
  - More efficient: matrix-matrix operations replace multiple matrix-vector operations
  - Can lead to better model parameters

Neural Networks

- Originally inspired by human neurons, but now simply an abstract computational device

- Can be thought of as combinations of neural units, where each unit multiplies input by a weight vector, adds a bias, and then applies a non-linear activation function

- Or alternatively as a computation graph

- Power comes from ability of early layers to learn representations (i.e. features) that can be used by later layers in the network

Neural Networks

- Choices in network structure
  - Width and depth
  - Choice of activation function
- Feedforward networks (no loop)

- Forward Propagation: predictions are made as a sequence of simple operations
  - matrix-vector operations
  - non-linear activation functions
- Training with the back-propagation algorithm
  - Requires defining a loss/error function
  - Gradient descent + chain rule
  - Easy to implement on top of computation graphs