Analyzing Software using Deep Learning

Introduction

Subscribe to the course via Piazza:
piazza.com/tu-darmstadt.de/summer2017/20000999iv

Prof. Dr. Michael Pradel

Software Lab, TU Darmstadt

About Me

- **Michael Pradel**
- **At TU Darmstadt since 2014**
- **Before joining TUDA**
  - Master-level studies in Dresden and Paris
  - Master thesis at EPFL, Switzerland
  - PhD at ETH Zurich, Switzerland
  - Postdoctoral researcher at UC Berkeley, USA

About the Software Lab





- **My research group since 2014**
- **Focus: Tools and techniques for building reliable, efficient, and secure software**
  - Program analysis
  - Test generation
- **Thesis and job opportunities**

Plan for Today

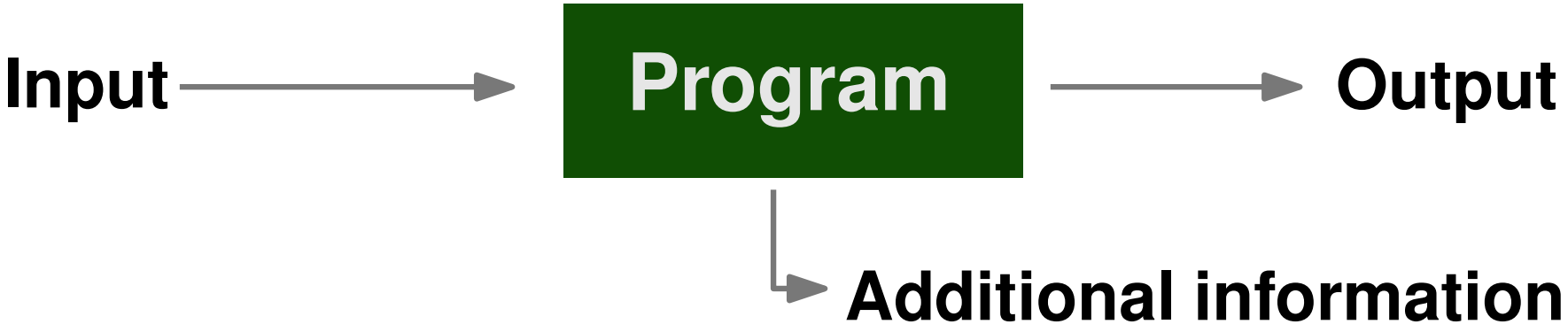
- **Introduction** ←
  - What the course is about
  - Why it is interesting
  - How it can help you
- **Organization**
  - Lectures and final exam
  - Course project
- **Basics**
  - Program analysis
  - Deep learning

What is Program Analysis?

- **Automated analysis of program behavior, e.g., to**
  - find programming errors
  - optimize performance
  - find security vulnerabilities

What is Program Analysis?

- **Automated analysis of program behavior, e.g., to**
  - find programming errors
  - optimize performance
  - find security vulnerabilities



What is Program Analysis?

- **Automated analysis of program behavior, e.g., to**
  - find programming errors
  - optimize performance
  - find security vulnerabilities

Why Do We Need It?

Basis for various tools that make developers productive

- Compilers
- Bug finding tools
- Performance profilers
- Code completion
- Automated testing
- Code summarization/documentation

Traditional Approaches

- **Analysis has built-in knowledge about the problem to solve**
- **Significant human effort to create a program analysis**
  - Conceptual challenges
  - Implementation effort
- **Analyze a single program at a time**

Learning from Existing Data

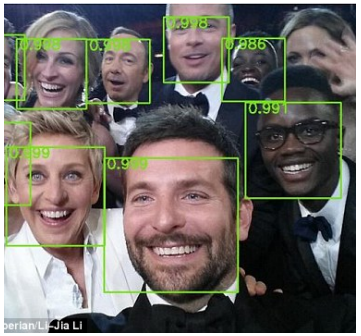
- **Huge amount of existing code ("big code")**
- **Programs are regular and repetitive**
- **Machine learning: Extract knowledge and apply in new contexts**
- **Learn how to ..**
  - .. complete partial code
  - .. use an API
  - .. fix programming errors
  - .. create inputs for testing

Deep Learning

Class of machine learning algorithms

- Neural network architectures
- ”Deep” = multiple layers
- Features and representation of inputs are extracted automatically

Revolutionizes entire areas



AlphaGo

This Course

Intersection of program analysis and deep learning

- Some of the basics:
  E.g., program representations, neural network architectures
- Recent research results:
  Based on recent research papers
- Hands-on experience:
  Coding project

Not This Course

What this course is not about

- Detailed coverage of program analysis
- Detailed coverage of machine learning
- Programming tutorial for TensorFlow

Check out related courses

- E.g., ”Program Testing and Analysis” (winter semester)

Plan for Today

- **Introduction**
  - What the course is about
  - Why it is interesting
  - How it can help you
- **Organization** ←
  - Lectures and final exam
  - Course project
- **Basics**
  - Program analysis
  - Deep learning

Organization

- **Weekly meetings**
  - 6 lectures
  - 4 Q&A sessions for course project
- **Reading material**
- **2nd half of semester (from June 12):**
  - Course project
- **July 27: Submission of project**
- **Aug 16: Written exam**

Grading

50% written exam

- Content of lectures and reading material
- Open book, one hour
- Will test your understanding, not your memory

50% course project

- Effectiveness of your implementation
- Documentation and code quality

Piazza

Platform for discussions, in-class quizzes, and sharing additional material

- Please register and enroll for the class
- Use it for all questions related to the course
- Messages sent to all students go via Piazza (not TUCaN!)

Subscribe to the course via Piazza:
piazza.com/tu-darmstadt.de/summer2017/20000999iv

Learning Material

There is no script or single book that covers everything

- Slides and hand-written nodes:
  Available after lecture
- Pointers to papers, book chapters, and web resources

Course Project

- **Individual project**
- **Same task for everybody**
- **Implement and evaluate a neural network that predicts/generates code**
- **Based on existing tools**
  - TensorFlow library for machine learning
  - Python
- **More details on June 12**

Plan for Today

- **Introduction**
  - What the course is about
  - Why it is interesting
  - How it can help you
- **Organization**
  - Lectures and final exam
  - Course project
- **Basics** ←
  - Program analysis
  - Deep learning

Program Analysis

Many ways to represent (parts of) a program

- Sequence of characters
- Sequence of tokens
- Abstract syntax tree
- Control flow graph
- Call graph
- etc.

Program Analysis

Many ways to represent (parts of) a program

- Sequence of characters
- Sequence of tokens
- Abstract syntax tree
- Control flow graph
- Call graph
- etc.

Tokens

Tokenizer (or lexer)

- Part of compiler
- Splits sequence of characters into subsequences called tokens

E.g., for Java, six kinds of tokens:

- Identifiers, e.g., `MyClass`
- Keywords, e.g., `if`
- Separators, e.g., `.` or `{`
- Operators, e.g., `*` or `++`
- Literals, e.g., `23` or `"hi"`
- Comments, e.g., `/* bla */`

Tokens: Example

```
if ( flag == true ) {
    name = "foe" ;
}
```

Identifier

Keywords

Separators

Operators

Literal

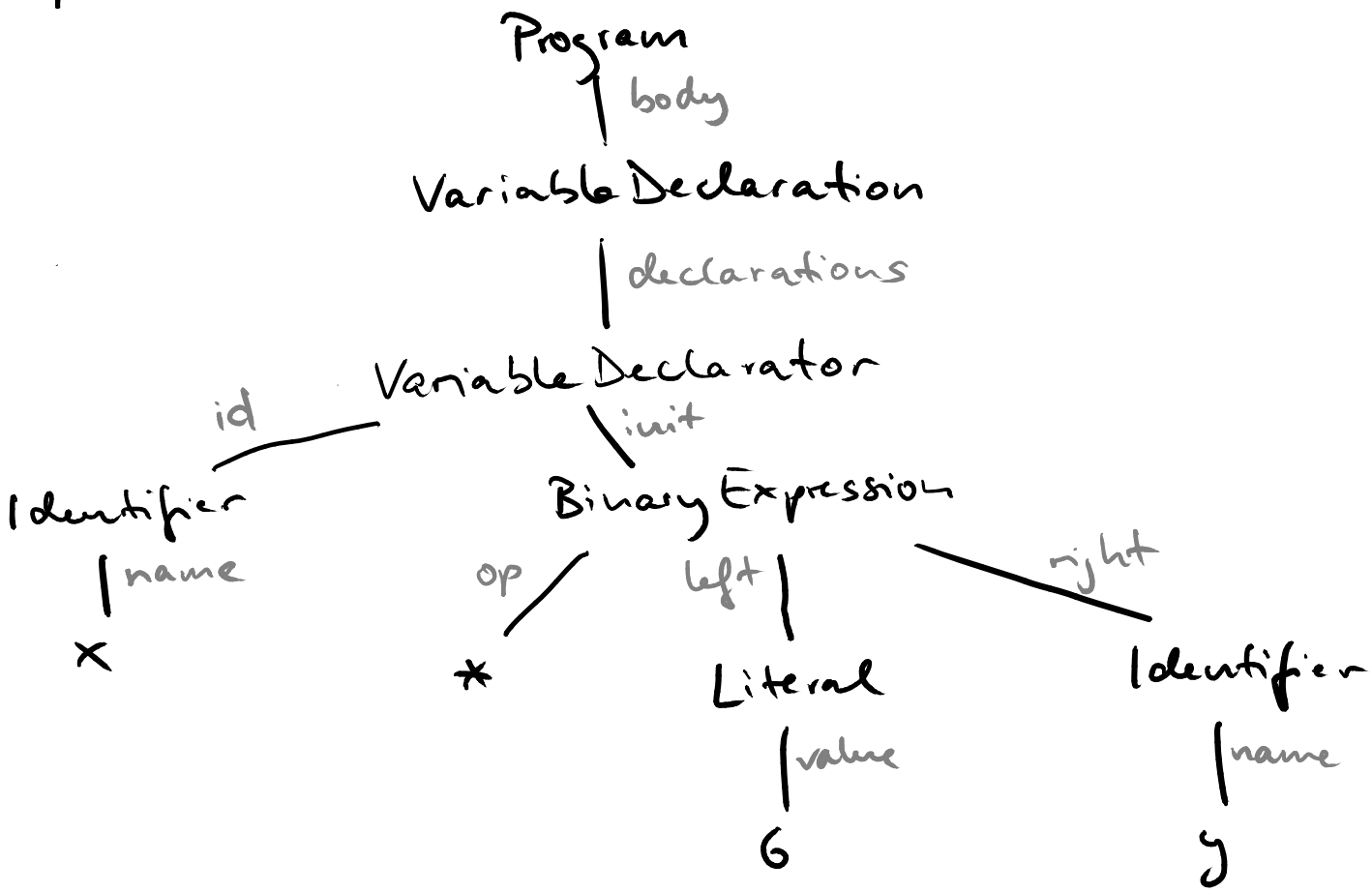
Abstract Syntax Tree

- **Tree representation of source code**
- **”Abstract” because some details of syntax omitted**
  - E.g., { in Java
- **Nodes: Construct in source code**
- **Edges: Parent-child relationship**
- **Check out Esprima for obtaining ASTs of Javascript: http://esprima.org/demo**

Abstract Syntax Trees: Example

Example: JavaScript

```
var x = 6 * y;
```



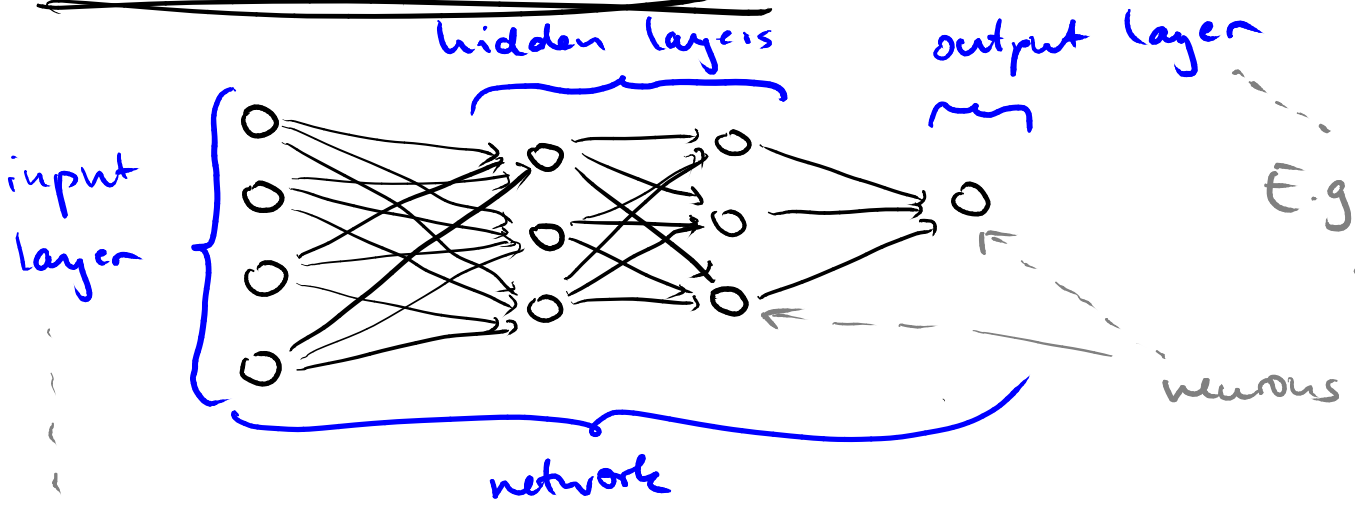
Deep Learning: Example

Example: Handwriting recognition

- Goal: Recognize digits 0..9
- Easy for a human but challenging for a computer
- Idea: Learn from a large number of training examples
- Deep learning: $> 99\%$ accuracy

Following slides based on Chapter 1 of neuralnetworksanddeeplearning.com

Networks of Neurons

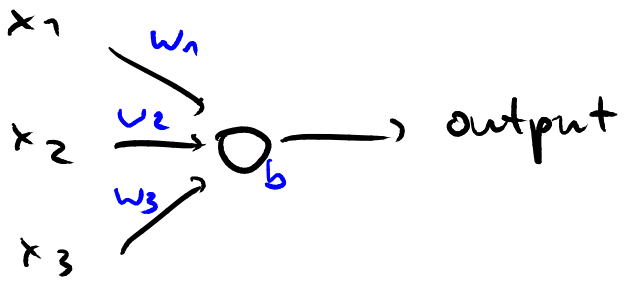


E.g., whether it's the digit 3.

E.g., pixel of an image

Perceptrons

Most basic kind neuron: Perceptron
↳ binary inputs
↳ binary output



What's the output?

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j \cdot x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j \cdot x_j > \text{threshold} \end{cases}$$

$$= \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

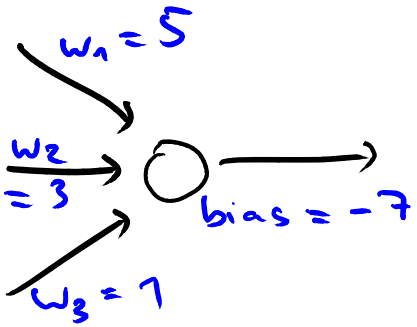
w.. weights
b.. bias

Example

x_1 = Weather is good

x_2 = Friends go

x_3 = Like cheese



output = Go to cheese festival

Assume $x_1 = 1$, $x_2 = 1$, $x_3 = 0$

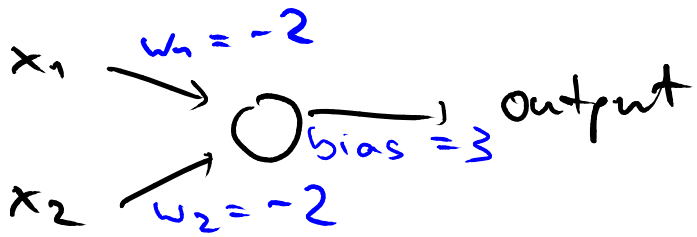
Quiz: output ?

$$w \cdot x = 5 \cdot 1 + 3 \cdot 1 + 1 \cdot 0 = 8$$

$$\text{output} = \begin{cases} 0 & \text{if } 8 - 7 \leq 0 \\ 1 & \text{if } 8 - 7 > 0 \end{cases} \longrightarrow \text{Go to festival}$$

Computing Logical Functions

NAND gate



x_1	x_2	output	
0	0	1	because $0 + 3 > 0$
0	1	1	because $-2 + 3 > 0$
1	0	1	— " —
1	1	0	because $-2 - 2 + 3 \leq 0$

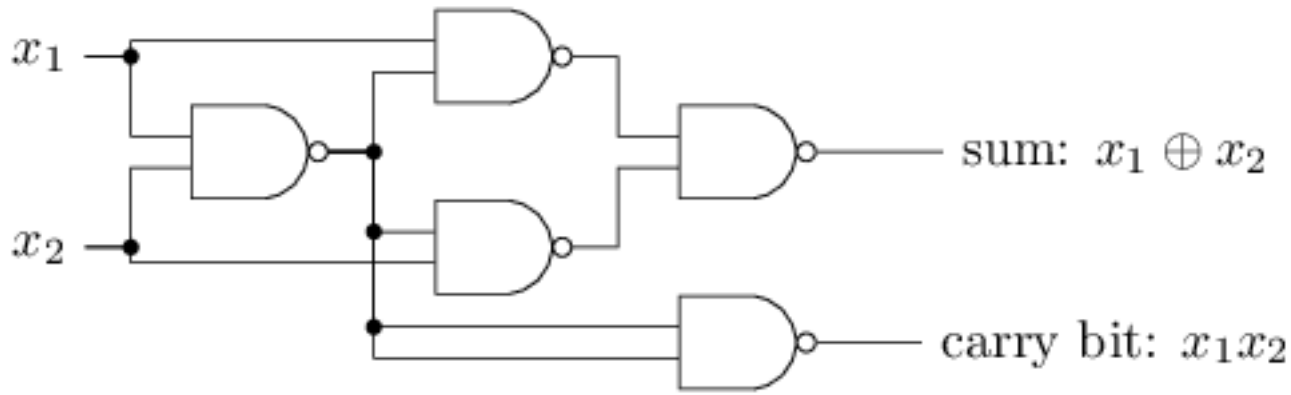
Universal Computation

- **Networks of NAND perceptrons can simulate every circuit containing only NAND gates**

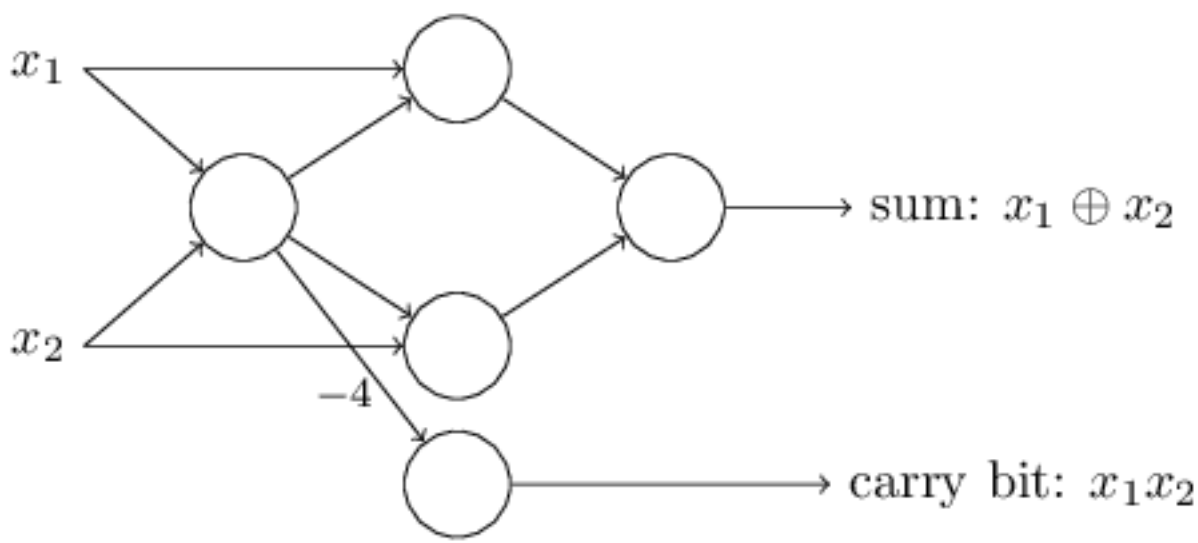
- **Can express arbitrary computations!**

Example: Adding Two Bits

NAND gate:



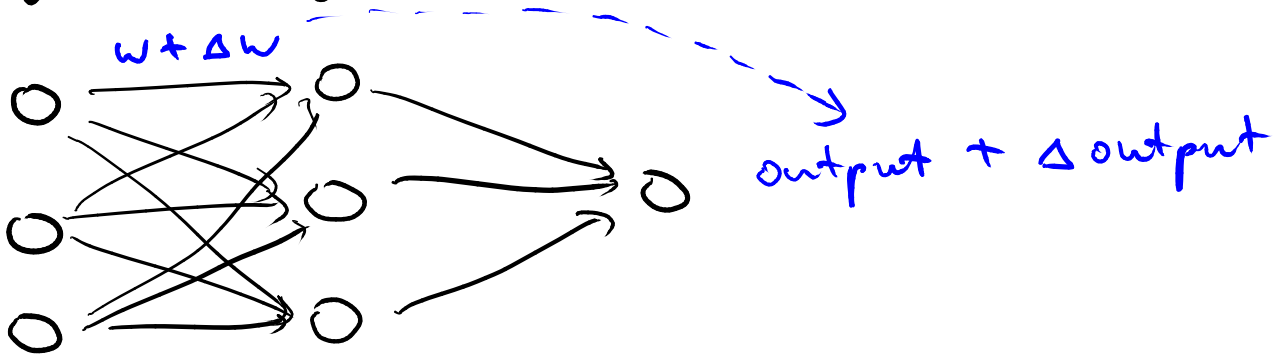
Network of perceptrons:



Challenge: Set Weights and Biases

- More complex networks can perform arbitrary computations
- How to decide on the weights and biases?
- Option 1: Hand-tune them
  $\rightarrow$ Infeasible for complex networks
- Option 2: Learn them
  $\rightarrow$ Key idea behind machine learning with neural networks

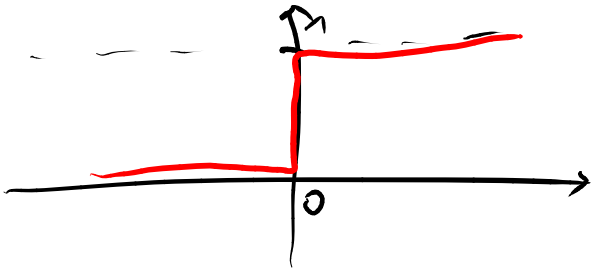
Making Learning Possible



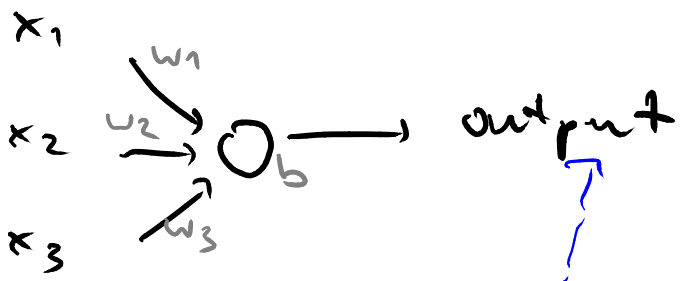
Want: Small Δ of weight or bias causes small change of output

Problem: Perceptron doesn't have this property

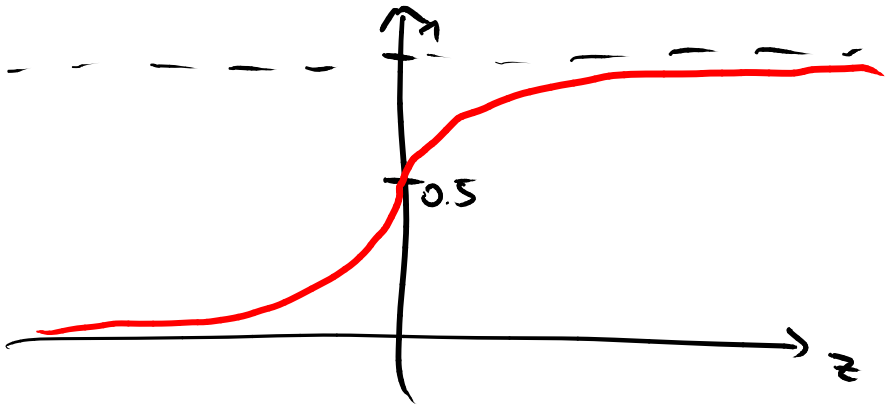
output = step (w · x + b)



Sigmoid Neuron



arbitrary values in $[0,1]$



$$\text{output} = \sigma(w \cdot x + b)$$

sigmoid fct.

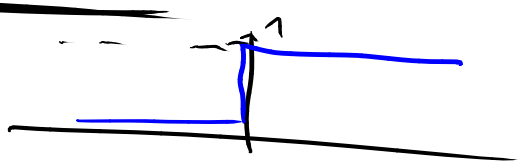
$$\sigma(z) \equiv \frac{1}{1+e^{-z}}$$

$$= \frac{1}{1+\exp\left(-\sum_j w_j x_j - b\right)}$$

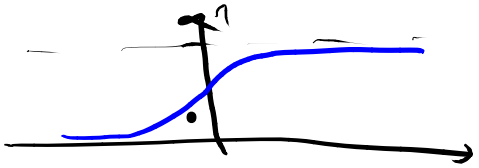
→ Enables learning:
Small change causes small change

Activation Functions

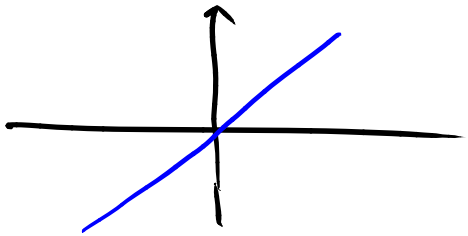
step function



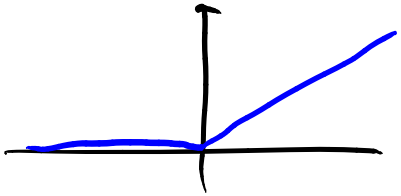
sigmoid / logistic function



identity fct.



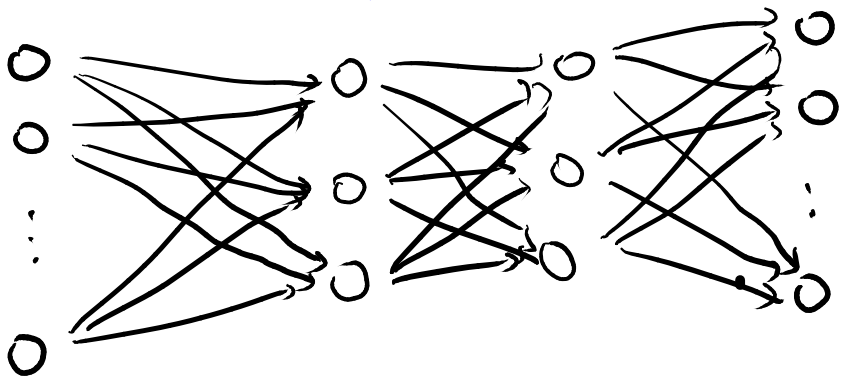
rectified linear unit



Different activation functions are useful in different kinds of networks

Networks of Neurons: Example

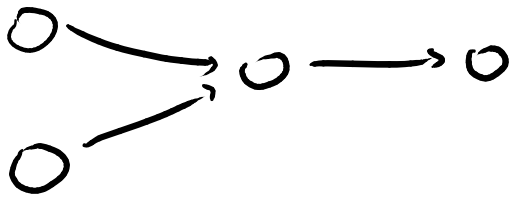
Example: Given image of digit, compute probability that digit is 0, ..., 9



Input layer:
28 × 28 inputs that represent grey scale value of a pixel

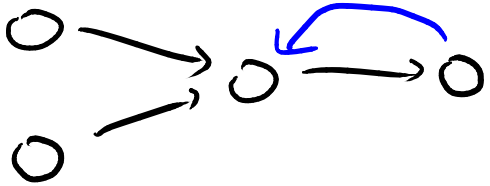
Output layer:
10 outputs that represent probab. that digit is 0, ..., 9

Feedforward Networks



- Output of layer $n-1$ is input to layer n
- No loops, information is never fed back.
- Useful if input-output pairs are indep. of each other
  - ↳ E.g., recognize digits

Recurrent Neural Networks

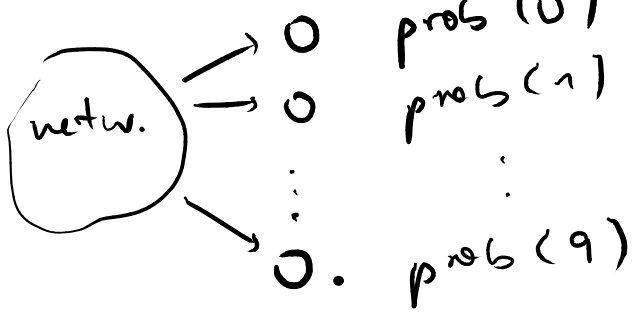


- Output of layer n may be fed back to layers $n, n-1, \ldots$
- Back edges serve as "memory"
- Useful for sequential information where inputs depend on each other

Learning: Cost Function

- Cost fct. = feedback on how good the output is for a given input

- Example:



If digit is known to be 6, want output

$$y(x) = (0, 0, 0, 0, 0, 0, 1, 0, 0, 0)^T$$

Actual output maybe:

$$a = (0, 0, 0, 0.2, 0, 0, 0.7, 0.1, 0, 0)^T$$

$$C(w, b) = \frac{1}{2 \cdot n} \cdot \sum_x \| y(x) - a \|^2$$

... quadratic cost fct. (or: mean squared error)

nb. of training inputs

desired output

output of network