technische universität
dortmund

DeepLearning on FPGAs

Introduction to Data Mining

Sebastian Buschjäger

Technische Universität Dortmund - Fakultät Informatik - Lehrstuhl 8

October 11, 2017

Structure of this course

Goals

→ Learning the basics of Data Mining
→ Learning the basics of Deep Learning
→ Learning the basics of FPGA programming

[1] https://www.kaggle.com/c/dogs-vs-cats-redux-kernels-edition/

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Small lecture-phase in the beginning

- **Week 1 - 3:** Data Mining and Deep Learning
- **Week 4 - 5:** FPGAs and Software

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Goal Dogs vs. Cats Kaggle competition[1]

- Image classification on FPGA with Deep Learning
- Train classifier on FPGA with Deep Learning

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The Goal: Predict dogs and cats

Overall Computer Science Approach

Technical Problem	Mathematical problem formulation
↓	
Mathematical Method	Theoretical method to solve problem
↓	
Algorithm	Theoretical algorithm implementing method
↓	
Implementation	Actual implementation

Overall Computer Science Approach: Example

Technical Problem	Best route from v_s to n_e in graph
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Implementation	`C,Java,Python,...`

Data Mining Basics

What is Data Mining?

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Example: Find all cats on the given pictures
$\rightarrow$ What is a mathematical representation of a cat?

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Example: Find all cats on the given pictures
$\rightarrow$ What is a mathematical representation of a cat?

Idea: Formalise given problem by positive and negative examples
$\rightarrow$ That is our data

Data Mining Basics

Problem 1: Data needs to be gathered and pre-processed
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Data Mining is an interdisciplinary field of:

- computer science: algorithm, theory, data structure, algorithm implementation, data warehousing, ...
- statistics: algorithm, theoretical insights, modelling, ...
- domain specifics: theoretical and practical insights, special knowledge, ...

Our focus: Mostly implementation and algorithms

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Data Mining: Problems

Our focus: Classification

Given:

- Set of possible classes $\mathcal{Y}$, e.g. $\mathcal{Y} = \{-1, +1\}$
- Set of labelled training examples / data
  $\mathcal{D} = \{(\vec{x}_1, y_1), \ldots, (\vec{x}_N, y_N) \mid (\vec{x}_i, y_i) \in \mathcal{X} \times \mathcal{Y}\}$
- A model $f_\theta : \mathcal{X} \to \mathcal{Y}$ with parameter $\theta \in \Theta$

Find: $\widehat{\theta}$, so that $f_{\widehat{\theta}}(\vec{x}) = \widehat{f}(\vec{x})$ that predicts class y for given $\vec{x}$

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Note 1: If $|\mathcal{Y}| = 2$ its called binary classification
Note 2: If $\mathcal{Y} = \mathbb{R}$ its called regression
Our focus: Binary classification: $\mathcal{Y} = \{0, +1\}$ or $\mathcal{Y} = \{-1, +1\}$

Data Mining: Notation

Note: The input space can be (nearly) everything
Our focus: $d-$dimensional vectors: $\vec{x} \in \mathcal{X} \subseteq \mathbb{R}^n$

$\mathcal{D}$	Feature 1	Feature 2	...	Feature d	Label
Example 1	x_{11}	x_{12}	$\dots$	x_{1d}	y_1
Example 2	x_{21}	x_{22}	$\dots$	x_{2d}	y_2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
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Matrix $X \in \mathbb{R}^{d \times N}$

Vector $\vec{y} \in \mathcal{Y}^N$

then: in short $\mathcal{D} = (X, \vec{y})$

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Observation

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Maybe simplest model

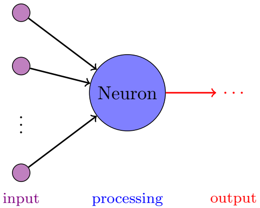
$$f(\vec{x}) = \begin{cases} +1 \text{ if } x_i > c \\ -1 \text{ else} \end{cases}$$

Thus $\theta = (i, c)$
But Which feature is important?
Again simple Just use all

Artificial Neural Networks: Single Neuron

Simple case: Let $\vec{x} \in \mathbb{B}^d$

Biology's view:



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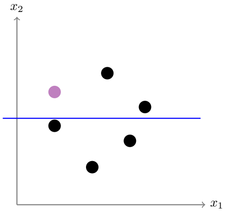

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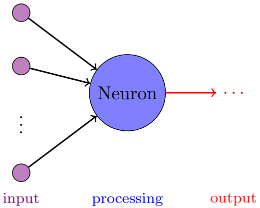

"Fire" if input signals reach threshold:

$$f(\vec{x}) = \begin{cases} +1 & \text{if } \sum_{i=1}^{d} x_i \geq b \\ 0 & \text{else} \end{cases}$$

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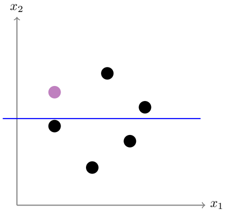

Predict class depending on side of line (count):

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Note: We basically count the number of positive inputs
1943: McCulloch-Pitts Neuron:

- Simple linear model with binary input and output
- Can model boolean OR with $b = 1$
- Can model boolean AND with $b = d$
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Remark: That does not help with classification, thus

- **Rosenblatt 1958:** Use weights $w_i \in \mathbb{R}$ for every input $x_i \in \mathbb{B}$
- **Minksy-Papert 1959:** Allow real valued inputs $x_i \in \mathbb{R}$

Artificial Neural Networks: Perceptron

A perceptron is a linear classifier $f\colon \mathbb{R}^d \rightarrow \{0,1\}$ with

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Linear function in $d = 2$: $y = mx + \tilde{b}$
Perceptron: $w_1 \cdot x_1 + w_2 \cdot x_2 \geq b \Leftrightarrow x_2 = \frac{b}{w_2} - \frac{w_1}{w_2} x_1$
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Note: $\vec{w} = (w_1, \ldots, w_d, b)^T$ are the parameters of a perceptron
Notation: Given $\vec{x}$ we add a 1 to the end of it $\vec{x} = (x_1, \ldots, x_d, 1)^T$

$$\textbf{Then}: \quad \widehat{f}(\vec{x}) = \begin{cases} +1 & \text{if } \vec{x} \cdot \vec{w}^T \geq 0 \\ 0 & \text{else} \end{cases}$$

ANN: Perceptron Learning

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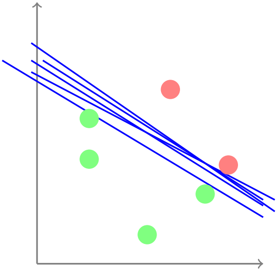

Note: We are happy with **one** separative vector $\vec{w}$

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Observation: We look at $\vec{x} \cdot \vec{w}^T \geq 0$

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$\vec{w} = rand(1, \ldots, d+1)$
while ERROR **do**
  for $(\vec{x}_i, y_i) \in \mathcal{D}$ **do**
    $\vec{w} = \vec{w} + \alpha \cdot \vec{x}_i \cdot (y_i - \widehat{f}(\vec{x}_i))$
  end for
end while

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5:     **end for**
6: **end while**

Note: $\alpha \in \mathbb{R}_{>0}$ is a stepsize / learning rate

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  $\rightarrow \vec{w}$ is decremented and classification is moved towards 0 ✓

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- Algorithm may have exponential runtime

Variation: Batch processing - Update $\vec{w}$ after testing all examples

$$\vec{w}_{new} = \vec{w}_{old} + \alpha \sum_{(\vec{x}_i, y_i) \in \mathcal{D}_{wrong}} \vec{x}_i \cdot (y_i - \widehat{f}_{old}(\vec{x}_i))$$

Usually: Faster convergence, but more memory needed

Overall Computer Science Approach

Technical Problem	Classification ✓
↓	
Mathematical Method	Linear classifier ✓
↓	
Algorithm	Perceptron learning ✓
↓	
Implementation	Actual implementation

Data Mining: Implementation of Perceptron Learning

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- **System:** CPU, GPU, FPGA, ...
- **Hardware:** Word length, cache sizes, vectorization, ...
- **Software:** Paging in OS, (Multi-) Threading, Swapping, ...
- **Language:** `C` vs. `Java` vs. `Haskell` ...

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But: Some systems / hardware is better at certain tasks
→ e.g. graphics cards are built to do matrix-vector multiplication

Thus: Choose method and algorithm depending on system
Our focus: Mostly methods and algorithms, later implementation

Overall Computer Science Approach

Technical Problem	Classification ✓
↓	
Mathematical Method	Perceptron ✓
↓	
Algorithm	Simple learning rule ✓
↓	
Implementation	System and language ✓

Data Mining: Measure Model quality

Fact 1: Prediction quality also depends on the algorithm, the implementation and the data
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Bottom line: Comparing specific methods is difficult
Thus: Compare performance of **computed** model

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Important: There is no free lunch (**Wolpert, 1996**)
→ Some methods work better on some problems, but no method works well on all problems

Data Mining: Measure Model quality (2)

Question: So, what is model quality?

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1. how well explains the model training data?
2. can we give any guarantees for new predictions?
3. how well generalises the model to new and unseen data?

So far Linear model assumption
No guarantees at all, especially if linear assumption does not hold

Data Mining: Measure Model quality (3)

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	Predicted value	
True value	True positive (TP)	False negative (FN)
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True value	True positive (TP)	False negative (FN)
	False positive (FP)	True negative (TN)

Accuracy: $Acc = \frac{TP+TN}{N}$

Big Remark: The accuracy only tells us something about the data $\mathcal{D}$ we know! There are no guarantees for new data

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Obviously: The best model has $Acc = 1$, the worst has $Acc = 0$
Observation: If we store all the data for look-up, then $Acc = 1$

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Clear: This is just memorizing the training data, no real learning!
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Idea: Split data into training $\mathcal{D}_{Train}$ and test data $\mathcal{D}_{Test}$
Then: $\mathcal{D}_{Test}$ is new to the model $f_{\widehat{\theta}}$
Question: How to split $\mathcal{D}$?

Data Mining: Measure Model quality (5)

1) Test/Train: Split $\mathcal{D}$ by size, e.g. 80% training and 20% test data
$\rightarrow$ Fast and easy to compute, but sensitive for “bad” splits.
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3) K-fold cross validation: Split data into k buckets. Use every bucket once for testing / train model on the rest. Average results.
$\rightarrow$ Insensitive for "bad" splits and practical. Usually $k = 10$.

Summary

Important concepts:

- **Classification** is one data mining task
- **Training data** is used to define and solve the task
- **A Method** is a general approach / idea to solve a task
- **A algorithm** is a way to realise a method
- **A model** forms the extracted knowledge from data
- **Accuracy** measures the model quality given the data

Summary

Important concepts:

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Note: Runtime and model quality depend on method, algorithm and implementation

Some administration stuff

Requirements to pass this course

- Plan an approach to solve kaggle competition including
  - Data pre-processing
  - Implementation of Neural Network learning
  - Incorperate FPGA design
- Give a small presentation / review about your approach

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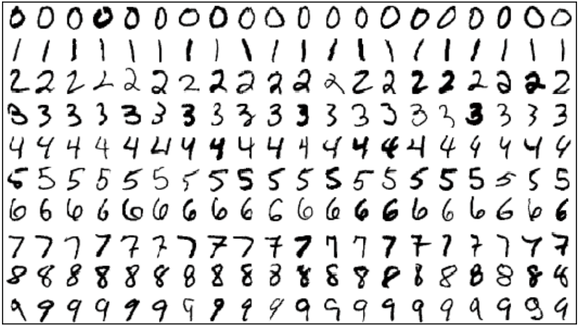
Thus: After the lecture phase you are free to do what you want until the end of the semester → you work in self-organizing groups

Question: When will we meet again for lectures?

Homwork Data

For development Use smaller data set

- 32×32 pixel grayscaled images of numbers $0 - 9$ $(10$ labels$)$
- already pre-processed in CSV format
- test/train split plus a smaller sample for development



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Homework until next meeting

- Implement a simple CSV-Reader
  - First column contains the label $(0 - 9)$
  - Remaining 784 columns contain grayscale value $(0 - 255)$
- Implement perceptron learning algorithm for two numbers
- Implement accuracy computation for Test/Train split

Note 1: We will later use `C`, so please use `C` or a `C`-like language
Note 2: Use the smaller split for development and the complete data set for testing $\rightarrow$ What's your accuracy?