DeepLearning on FPGAs

Introduction to Data Mining

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October 18, 2016

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 - 4:** Data Mining and Deep Learning
- **Week 4 - 6:** 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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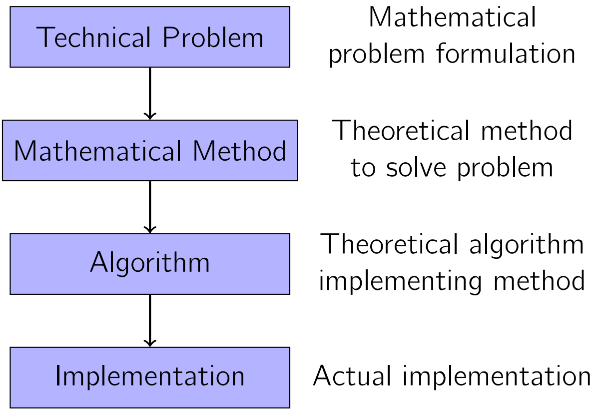
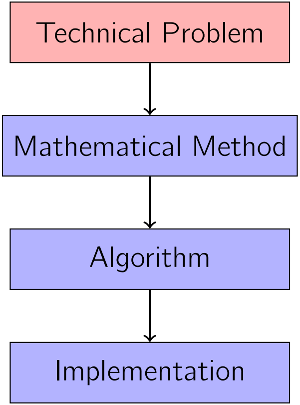
The Goal: Predict dogs and cats

Overall Computer Science Approach



Overall Computer Science Approach: Example



Best route from v_s to n_e in graph

Theoretical method to solve problem

Theoretical algorithm implementing method

Actual implementation

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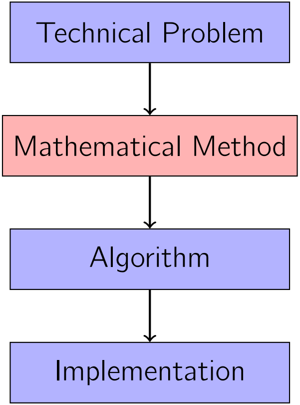

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Single source shortest path problem

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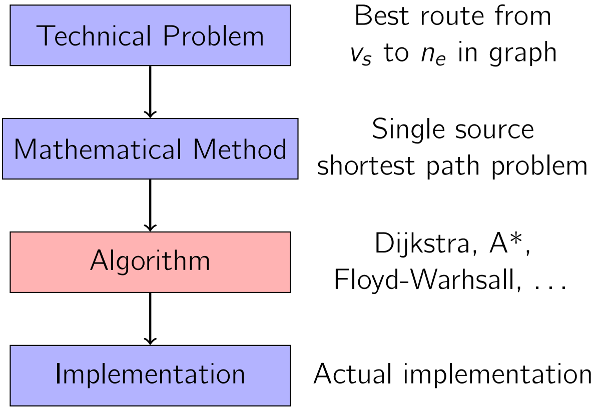

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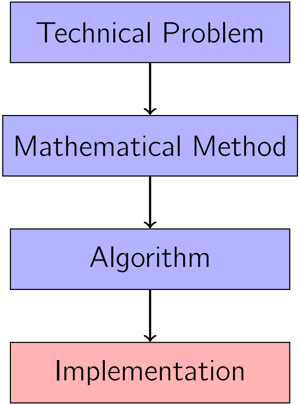

Best route from
v_s to n_e in graph

Single source
shortest path problem

Dijkstra, A*,
Floyd-Warhsall, ...

`C,Java,Python,...`

Data Mining Basics

What is Data Mining?

Data Mining Basics

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$\rightarrow$ 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

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→ crawling the web for images with tag "cat"

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$\rightarrow$ cats and dogs can be on the same picture

$\Rightarrow$ We have to "mine" data and knowledge from it

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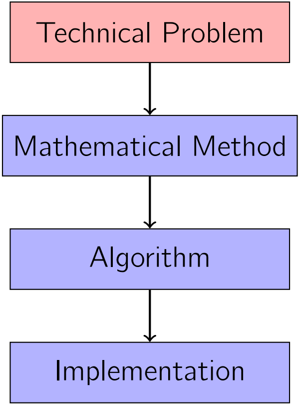
Data Mining is an interdisciplinary field of:

- 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

Overall Computer Science Approach



Data Mining problems

Theoretical method
to solve problem

Theoretical algorithm
implementing method

Actual implementation

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
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Example N	x_{N1}	x_{N1}	$\dots$	x_{Nd}	y_N

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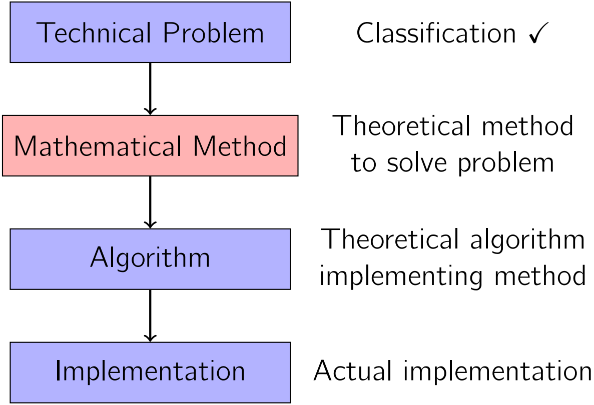
Matrix $X \in \mathbb{R}^{d \times N}$

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

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

Overall Computer Science Approach



Data Mining: K nearest neighbour method

Obviously: We want a prediction method $\widehat{f}(\vec{x})$
Observation: Examples $\vec{x}_i$ and $\vec{x}_j$ which are similar probably have the same label $y_i = y_j$

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Idea: Given new and unseen observation $\vec{x}$

- use distance function $dist\colon \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$
- calculate $d(\vec{x}, \vec{x}_i)$ for all $i = 1, \ldots, N$
- find k nearest neighbours of $\vec{x}$ $S = \{(\vec{x}_1, y_1), \ldots, (\vec{x}_k, y_k)\}$
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Note: If S has equal number of positive and negative examples, take a random class

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K-NN has two parameters

- *dist* Models the distance of neighbours. This must fit the data given! Usually euclidean norm is a good start:

$$dist(\vec{x}_i, \vec{x}_j) = \sqrt{(\vec{x}_i - \vec{x}_j)^T \cdot (\vec{x}_i - \vec{x}_j)}$$

- K Models the number of neighbours we want to look at.

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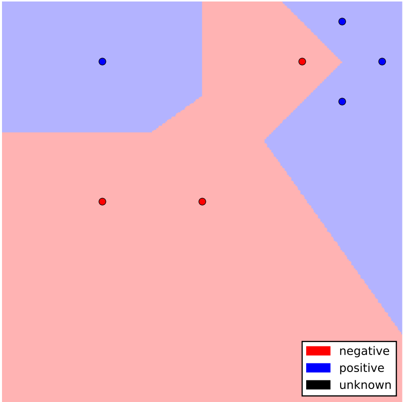
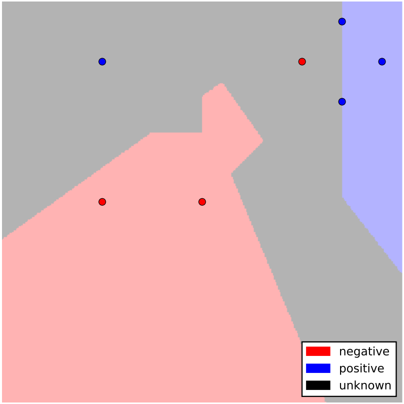
Note 2: K-NN can be used for regression as well. Just average the labels in S :

$$\widehat{f}(\vec{x}) = \frac{1}{k} \sum_{y \in S} y$$

Data Mining: K-NN Examples

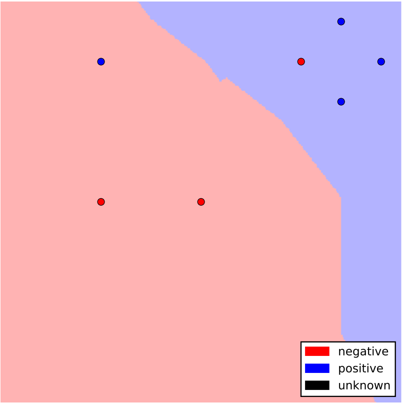


$k = 1$

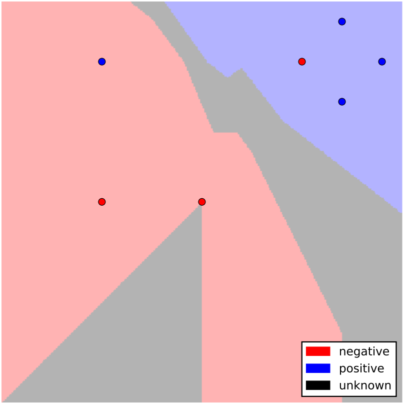


$k = 2$

Data Mining: K-NN More examples

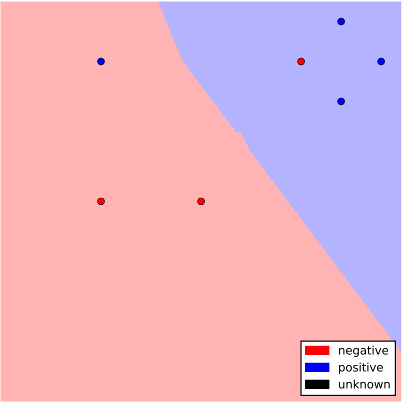


$k = 3$

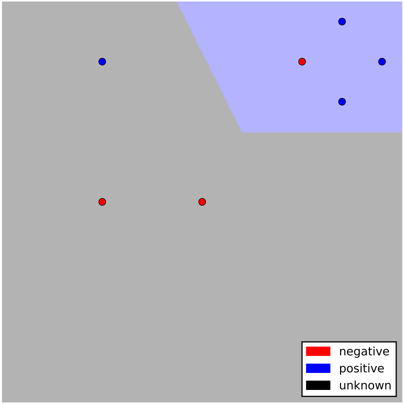


$k = 4$

Data Mining: K-NN Even more examples

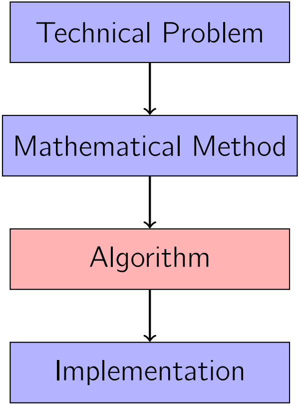


$k = 5$



$k = 6$

Overall Computer Science Approach



Classification ✓

K-NN ✓

Theoretical algorithm implementing method

Actual implementation

Data Mining: Naive K-NN algorithm

Let: $\vec{x}^*$ be new unobserved data to be classified

$S = \emptyset$
for $i = 1, \ldots, K$ **do**
    for $\vec{x} \in X$ **do**
        if $d(\vec{x}^*, \vec{x}) < min$ and $\vec{x} \notin S$ **then**
            $min = d(\vec{x}^*, \vec{x})$
            $\vec{x}_{min} = \vec{x}$
        end if
        $S = S \cup \{\vec{x}_{min}\}$
    end for
end for

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```
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        end if
        S = S ∪ {x⃗_min}
    end for
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```

Computation in $O(d)$ — refers to $d(\vec{x}^*, \vec{x})$

Lookup in $O(K)$ — refers to $\vec{x} \notin S$

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Computation in $O(d)$

Lookup in $O(K)$

Worst Case runtime: $O(K^2Nd)$ for every new example!

Data Mining: More intelligent K-NN algorithm (1)

We want: Extract model $\widehat{\theta}$ once, then apply it

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Idea: Pre-process $\mathcal{D}$ ($\rightarrow$ data structures), so that fast retrival of neighbours is possible $\Rightarrow$ "Fast nearest neighbour search"
Thus: Training time increases, but queries are faster

Data Mining: More intelligent K-NN algorithm (2)

Fact: There are many algorithms realising this idea

- **Tree structures:** k-d tree, quadtree, range tree, ...
- **Locality Sensitive Hashing:** Random projection, TLSH, ...
- **Approximative Nearest Neighbour:** Best bin first, LSH, ...

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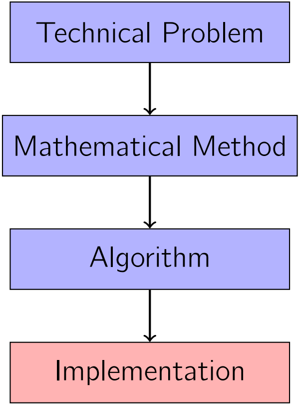
Usually we expect for the average case:

- **Pre-processing:** $O(Nd\log(Nd))$
- **Queries:** $O(Kd\log(N))$

Bottom line: The runtime not only depends on the method, but also the algorithm realising it

Overall Computer Science Approach



Classification ✓

K-NN ✓

Brute force
trees, hashing ✓

Actual implementation

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Obviously: Implementation also influences the runtime!

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Fact: We need to take the underlying system into account

- **System:** CPU, GPU, FPGA, ...
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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 ↓	K-NN ✓
Algorithm ↓	Brute force trees, hashing ✓
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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Important: There is no free lunch (**Wolpert, 1996**)
→ Some methods work better on some problems, but no method works well on all problems

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→ does not explain the data at all

2: K-NN assumes similarity depending on the distance function
→ no guarantees at all, especially if distance function does not fit

Data Mining: Measure Model quality (3)

Fact: In binary classification we have two choices: predict 0 or 1
$\rightarrow$ 2 possible wrong predictions and 2 possible correct predictions

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Visualization: Confusion matrix

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	Predicted value	
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 $Acc = 0$
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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 and 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

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

So far: K-NN is one method with many different algorithms and implementations to solve classification problems

Some administration stuff

Requirements to pass this course:

- Implement your own neural network for the FPGA
- Apply it to the data of the kaggle competition
- Give a small presentation / review about your approach

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?

Homework: I give some simple homeworks to get you started more easily → We will use the MNIST dataset for that

- 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

Homework

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 accuracy computation for Test/Train split
  - We discussed the binary confusion matrix (4 entries)
  - Here 10 classes: Only diagonal of the confusion matrix needed for the accuracy → just count correct classifications and divide it by the total number of test examples
- Implement K-NN with distance function of your choice
  - Euclidean distance is a good start

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 → What's your accuracy?