DEEP LEARNING FUNDAMENTALS AND BASIC TOOLS

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Master's Program in Deep Learning for Audio and Video Signal Processing

COURSE PRESENTATION

Please read the course guide

LECTURERS

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LEARNING OUTCOMES

Upon completion of this course, you will be able to:

- Understand the fundamentals of DL within the ML learning context
- Train a DNN, choosing the most appropriate characteristics and optimizing the hyperparameters
- Describe the main architectures used in DL, as well as the most typical applications
- Identify the most appropriate DL algorithm for various types of problems in different domains
- Implement DL algorithms using different tools

COURSE CONTENTS

- Introduction to Deep Learning
- Machine learning fundamentals
- Neural Network basics:
  - Shallow neural networks
  - Backpropagation
- Deep Neural Networks:
  - Practical aspects of deep learning: activation functions, loss functions, weight initialization
  - Batch normalization.
  - Regularization techniques, dropout

- Optimization techniques:
  - Stochastic Gradient Descent
  - Adaptive methods
- Hyper-parameter tuning
- Deep learning architectures:
  - Convolutional neural networks
  - Recurrent neural networks
  - Autoencoders and GANs
- Deep Learning programming and parallelization tools: TensorFlow, Keras, PyTorch

BIBLIOGRAPHY

EVALUATION

- Final exam: 50%
- 3 laboratory assignments: 50%

SCHEDULE

Week	Contents	Labs
Week 1	Introduction Machine Learning Fundamentals Linear and Logistic Regression Gradient Descent	Lab 1
Week 2	Neural Networks Basics Shallow Networks Backpropagation	Lab 1

SCHEDULE

Week	Contents	Labs
Week 3	Deep Neural Networks Practical aspects of deep learning Batch normalization Regularization, dropout	Lab 2
Week 4	Optimization techniques: SGD, adaptive methods Hyper-parameter tuning	Lab 2

SCHEDULE

Week	Contents	Labs
Week 5	Deep learning architectures: Convolutional Neural Networks Recurrent Neural Networks	Lab 3
Week 6	Deep learning architectures: Autoencoders, GANs Deep RL **Final exam (Oct 20th, 16:00)**	Lab 3

ADDITIONAL RESOURCES

- Introduction to Deep Learning, MIT, http://introtodeeplearning.com/
- Convolutional Neural Networks for Visual Recognition, Stanford, http://cs231n.stanford.edu/
- TensorFlow tutorials, https://www.tensorflow.org/tutorials/
- TensorFlow Playground, http://playground.tensorflow.org
- PyTorch tutorials

RECOMMENDATIONS

- The following skills are highly recommended:
  - Calculus
  - Linear algebra
  - Statistics and probability theory
  - Python programming

WHAT IF I NEED TO REVIEW MATHS CONCEPTS?

- Chapters 2 and 3 of Goodfellow's book:
  - Linear algebra
  - Probability and information theory
- Linear Algebra Review and Reference, Zico Kolter, 2015

WHAT IF I NEED TO REVIEW PROGRAMMING CONCEPTS?

- Python Numpy Tutorial (with Jupyter and Colab), Justin Johnson

INTRODUCTION TO DEEP LEARNING

- What is deep learning?
- Why now?

WHAT IS DEEP LEARNING?

- A subfield of Machine Learning: learn without being explicitly programmed
- Make predictions on data using Neural Networks
- Deep neural networks: many layers

WHY DEEP LEARNING NOW?

- Lots of data
- Increase in computational power (parallelization, GPUs, …)
- New programming tools, algorithms and tricks

MACHINE LEARNING BASICS

Suggested reading:

https://www.deeplearningbook.org/contents/ml.html

WHAT IS MACHINE LEARNING?

- Field of study that gives computers the ability to learn without being explicitly programmed. (Attributed to A. Samuel, 1959)
- Subfield of AI that studies computer algorithms that improve automatically through experience. (Wikipedia, 2020)

DIFFERENT LEARNING TASKS

- Supervised machine learning
  - Classification
  - Regression
- Unsupervised machine learning
- Semi-supervised machine learning
- Reinforcement learning

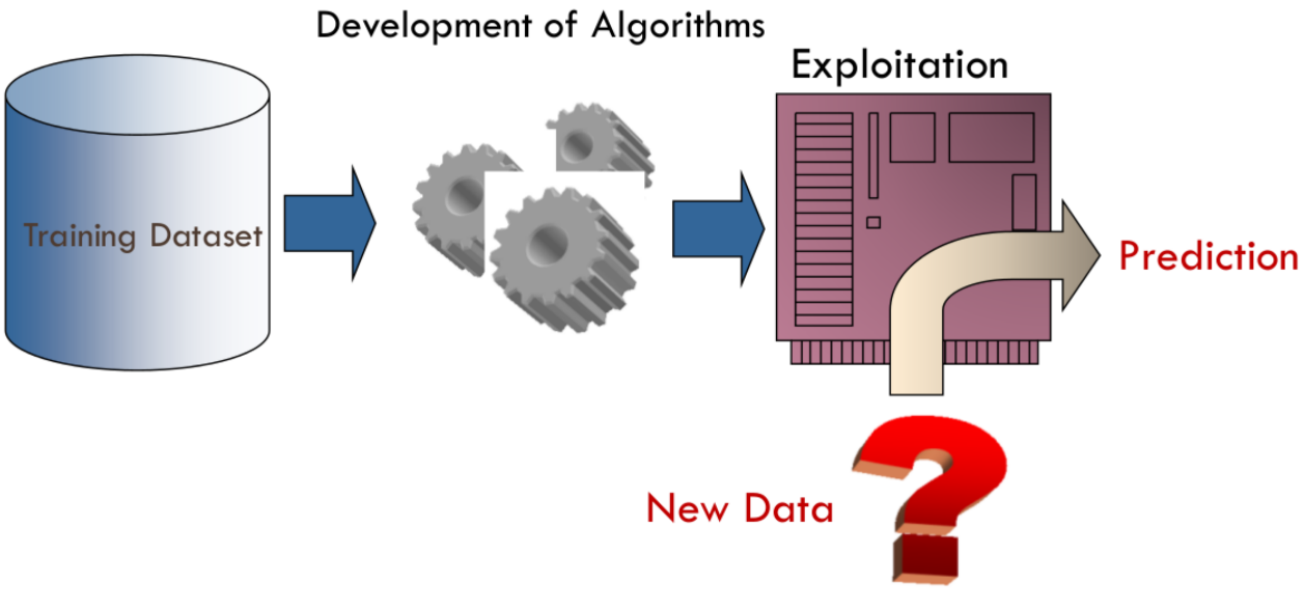
SUPERVISED MACHINE LEARNING - DEFINITIONS

- The problem data is the set of patterns $\{(\mathbf{x}_1, t_1), (\mathbf{x}_2, t_2), \ldots, (\mathbf{x}_n, t_n)\}$, where:
  - $\mathbf{x}_i$ is the attribute vector for pattern i
  - t_i is the target (variable to predict) for pattern i
  - n is the total number of patterns
- The goal is to predict the target t_i given the attribute vector $\mathbf{x}_i$

PARAMETRIC MODELS FOR CLASSIFICATION (REGRESSION)

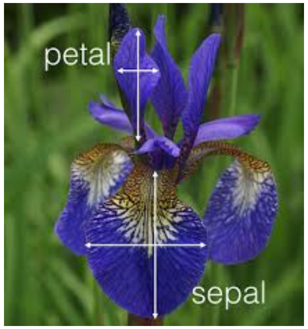
- A classifier (regressor) is a function $f(\mathbf{x}, \theta)$ that assigns each pattern $\mathbf{x}_i$ an estimation of its target value: $y_i = f(\mathbf{x}_i, \theta) \approx t_i$
- Model training: tune the model parameters θ in order to minimize a *loss function* $L(y_i, t_i)$
- Different function families define different types of models: Neural Networks, SVMs, etc.

SUPERVISED MACHINE LEARNING - OVERVIEW



SUPERVISED MACHINE LEARNING - AN EXAMPLE

The Iris plant dataset (R.A. Fisher, 1936)



- Classify Iris plant samples into 3 subspecies: *Setosa*, *Virginica* and *Versicolor*
- Use the width and length of petal and sepal as attributes

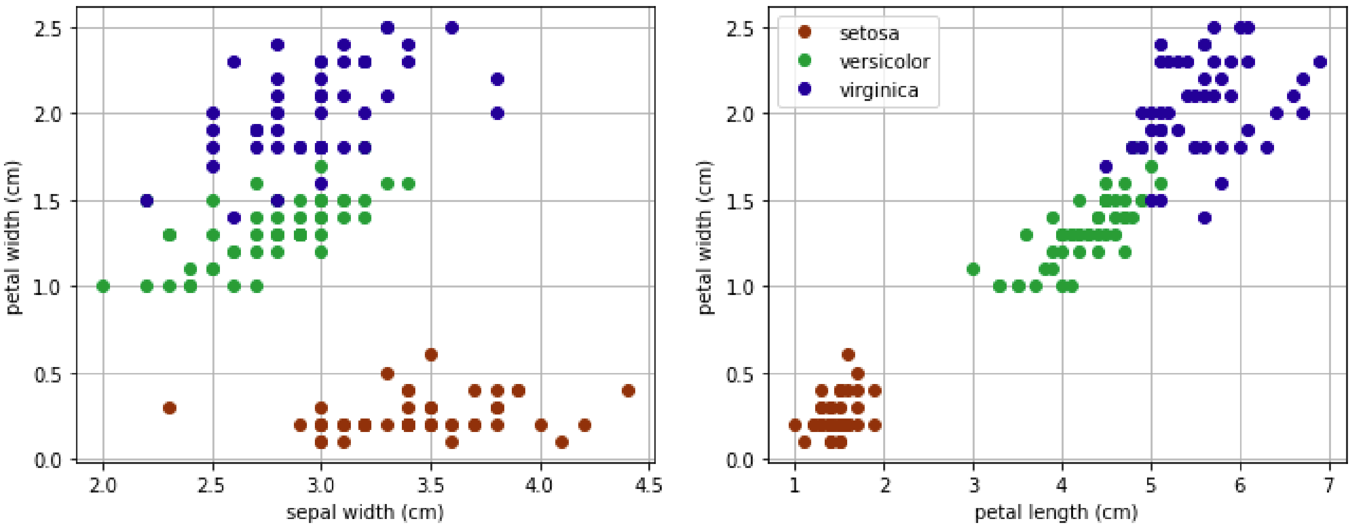
SUPERVISED MACHINE LEARNING - AN EXAMPLE

The Iris plant dataset (R.A. Fisher, 1936)

sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	target_num
5.1	3.5	1.4	0.2	setosa	0
5.4	3.7	1.5	0.2	setosa	0
5.4	3.4	1.7	0.2	setosa	0
4.8	3.1	1.6	0.2	setosa	0
5.0	3.5	1.3	0.3	setosa	0
7.0	3.2	4.7	1.4	versicolor	1
5.0	2.0	3.5	1.0	versicolor	1
5.9	3.2	4.8	1.8	versicolor	1
5.5	2.4	3.8	1.1	versicolor	1
5.5	2.6	4.4	1.2	versicolor	1
6.3	3.3	6.0	2.5	virginica	2
6.5	3.2	5.1	2.0	virginica	2
6.9	3.2	5.7	2.3	virginica	2
7.4	2.8	6.1	1.9	virginica	2
6.7	3.1	5.6	2.4	virginica	2

SUPERVISED MACHINE LEARNING - AN EXAMPLE

The Iris plant dataset (R.A. Fisher, 1936)



Classification or regression?

SUPERVISED MACHINE LEARNING - SECOND EXAMPLE

The Boston Housing problem

- Predict housing prices in the suburbs of Boston

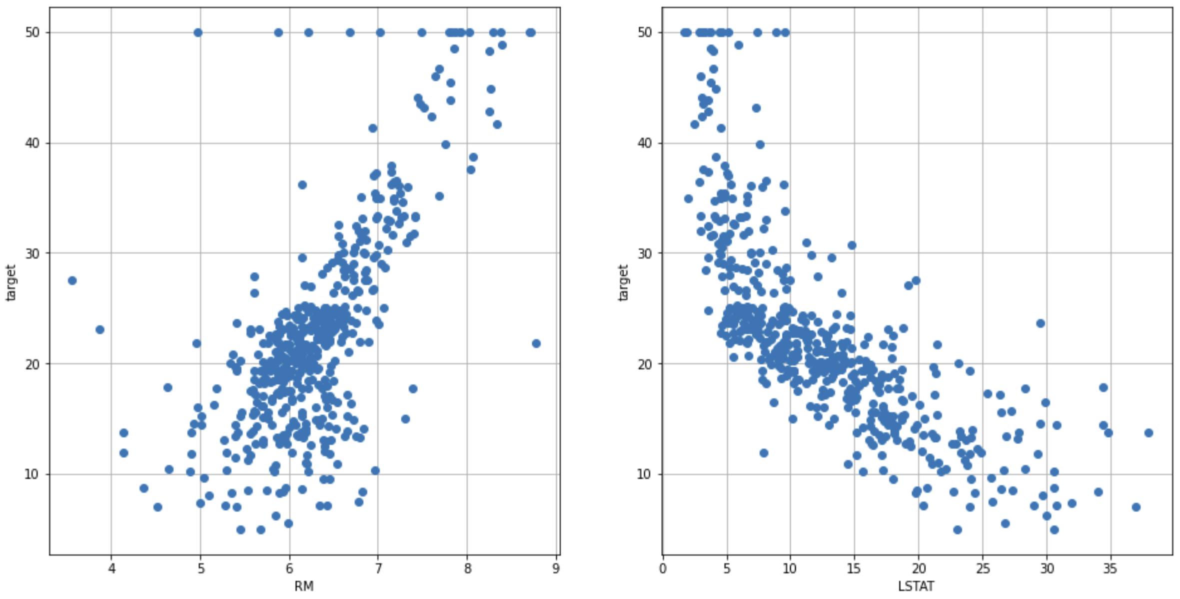
SUPERVISED MACHINE LEARNING - SECOND EXAMPLE

The Boston Housing problem

CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	target
0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
0.22489	12.5	7.87	0.0	0.524	6.377	94.3	6.3467	5.0	311.0	15.2	392.52	20.45	15.0
1.25179	0.0	8.14	0.0	0.538	5.570	98.1	3.7979	4.0	307.0	21.0	376.57	21.02	13.6
1.13081	0.0	8.14	0.0	0.538	5.713	94.1	4.2330	4.0	307.0	21.0	360.17	22.60	12.7
0.03359	75.0	2.95	0.0	0.428	7.024	15.8	5.4011	3.0	252.0	18.3	395.62	1.98	34.9
0.08873	21.0	5.64	0.0	0.439	5.963	45.7	6.8147	4.0	243.0	16.8	395.56	13.45	19.7
0.14932	25.0	5.13	0.0	0.453	5.741	66.2	7.2254	8.0	284.0	19.7	395.11	13.15	18.7
0.08826	0.0	10.81	0.0	0.413	6.417	6.6	5.2873	4.0	305.0	19.2	383.73	6.72	24.2
0.04113	25.0	4.86	0.0	0.426	6.727	33.5	5.4007	4.0	281.0	19.0	396.90	5.29	28.0
0.04684	0.0	3.41	0.0	0.489	6.417	66.1	3.0923	2.0	270.0	17.8	392.18	8.81	22.6
0.14866	0.0	8.56	0.0	0.520	6.727	79.9	2.7778	5.0	384.0	20.9	394.76	9.42	27.5
0.10793	0.0	8.56	0.0	0.520	6.195	54.4	2.7778	5.0	384.0	20.9	393.49	13.00	21.7
0.06899	0.0	25.65	0.0	0.581	5.870	69.7	2.2577	2.0	188.0	19.1	389.15	14.37	22.0
0.34006	0.0	21.89	0.0	0.624	6.458	98.9	2.1185	4.0	437.0	21.2	395.04	12.60	19.2
0.29090	0.0	21.89	0.0	0.624	6.174	93.6	1.6119	4.0	437.0	21.2	388.08	24.16	14.0

SUPERVISED MACHINE LEARNING - SECOND EXAMPLE

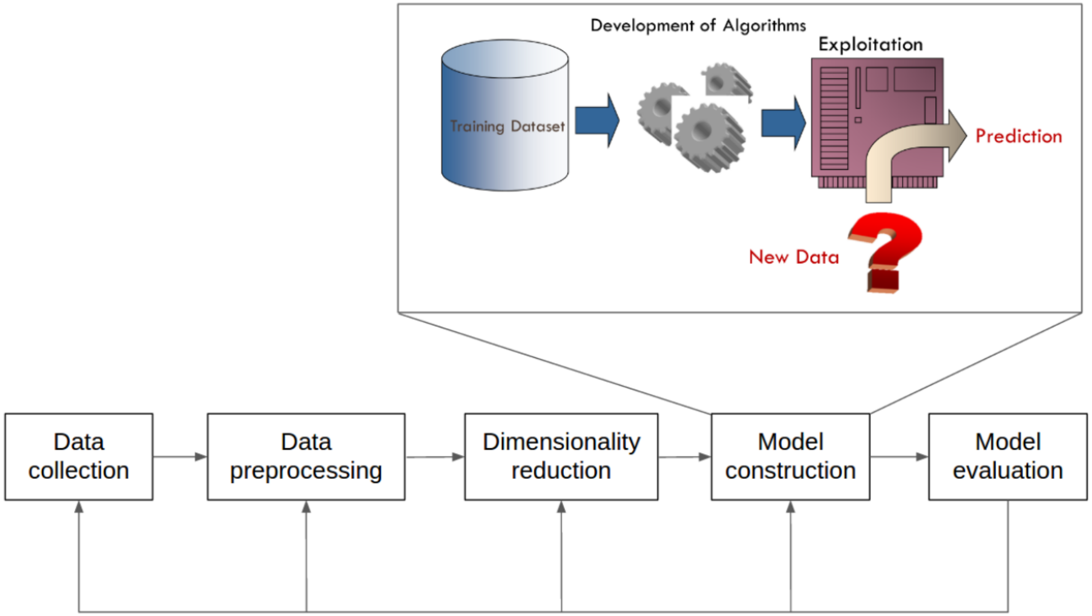
The Boston Housing problem



Classification or regression?

THE ML DESIGN CYCLE

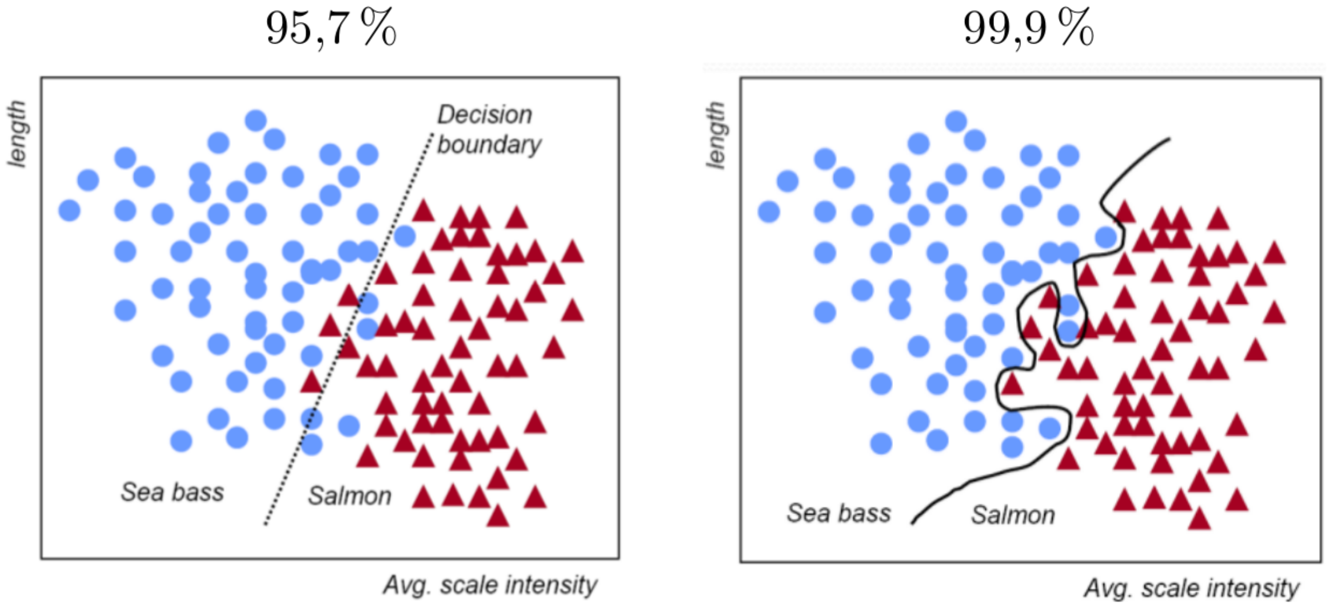
Model construction/training is just one single step in a much bigger process



MODEL EVALUATION AND SELECTION

- How to assess the quality of a trained model
- How to compare two different models
- Model validation and hyper-parameter tuning
- Different evaluation metrics: loss, accuracy, confusion matrix, ROC analysis, etc.

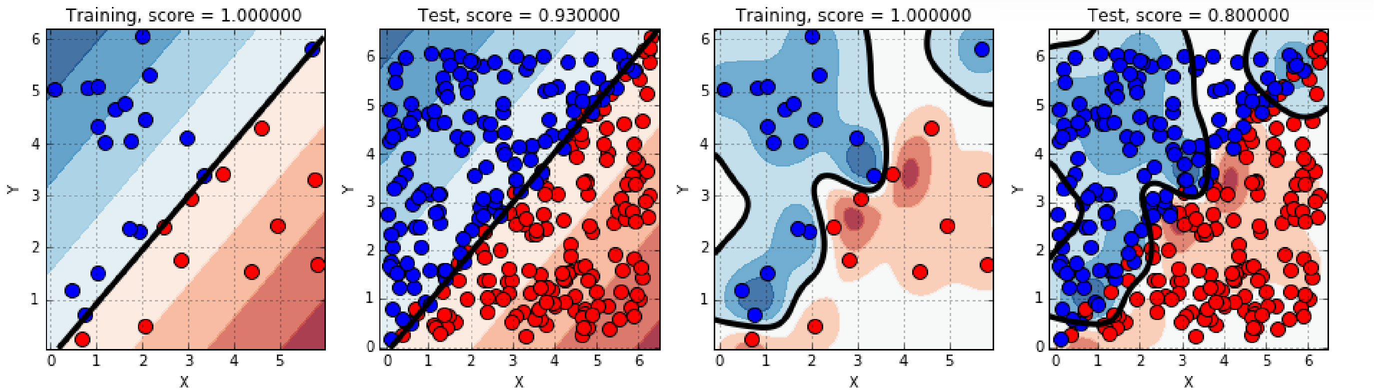
MODEL EVALUATION AND SELECTION - EXAMPLE



(From Duda, Hart and Stork, *Pattern Classification*, 2001)

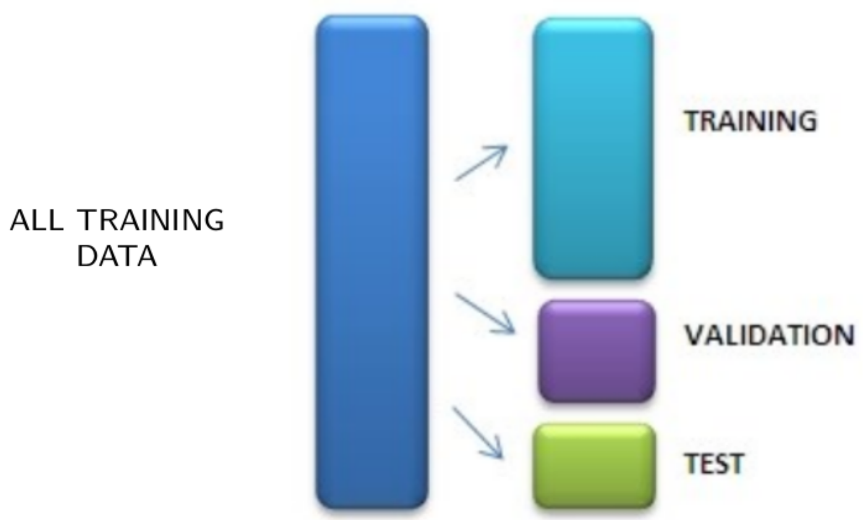
Which model is better?

MODEL COMPLEXITY AND GENERALIZATION



- Complex models are able to better adapt to the training data
- *Overfitting*: too much adaptation to the training data may lead to a poor generalization

TRAINING, VALIDATION, TEST



- Use different data for training and validating the model
- Early stoping

(PROPER) REGULARIZATION

- Modify the loss function by introducing a term that penalizes model complexity
- LOSS = ERROR + COMPLEXITY

REVIEW: CORE TOPICS

- DL is a subfield of ML that uses NNs to make predictions on data
- NNs are supervised, parametric models that learn from examples (classification, regression)
- Model training: tune the parameters in order to adapt to the training data
- Model validation: complexity, generalization, overfitting, regularization

NEXT DAY

- Neural networks with one single neuron
- Linear regression
- Logistic regression (classification)

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