

# Applied Machine Learning lecture 1

Introduction to Applied Machine Learning

*Pascal Mettes – University of Amsterdam*

*Lecturer of today: Thomas Mensink - Google*

# Agenda of the day

Welcome

Introduction

Course and syllabus

Regression I

# Welcome



PhD Computer Science @ Grenoble (France)

PostDoc researcher @ UvA

Assistant Professor @ UvA

**Research Scientist @ Google**

Research topics: 3D, Deep Learning, large scale image classification, machine learning, learning without examples.

# Lecturer

PhD Computer Science @ UvA

Visiting Researcher @ Columbia University, USA

PostDoc researcher @ UvA

Assistant professor @ UvA



Research topics: action recognition, action localization, deep learning, learning from limited supervision.





Hi





# Other people of the course



Cristian Rodriguez  
Rivero



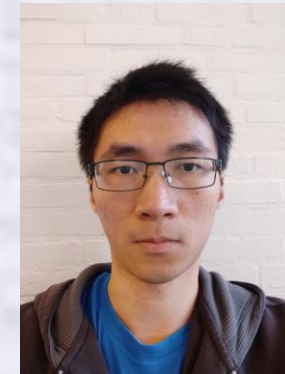
Ivan Sosnovik



Shi Hu

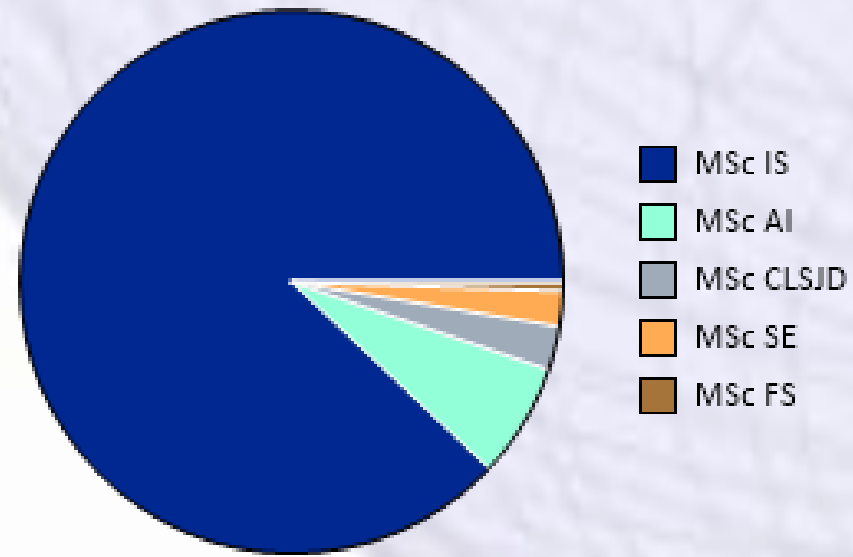


Sarah Ibrahimi



David Zhang

# Students



Admissions forcefully stopped at 173.

# Syllabus

Full pdf with course details available on canvas.

Syllabus states course details, deadline, and required reading materials.



# The course

				Math tutorial	Lab
1	44	Intro and Regression I	Regression II		Lab Intro
2	45	Classification I	Classification II	Math tutorial 1	Lab Assignment 1
3	46	Deep Learning I	Representing Images		Lab Assignment 2
4	47	Representing Text	Deep Learning II	Math tutorial 2 Peer feedback open questions	Kaggle-Project week 1
5	48	Setting up a ML system <i>Intro to Reinforcement Learning</i>	Recommender Systems		Kaggle-Project week 2
6	49	AI for industry and humanities	Autonomous driving	Math tutorial 3	Kaggle-Project week 3
7	50	Q&A			Kaggle-Project week 4
8	51	Exam			Poster/Demo Session

# The good, the bad, and the ugly

# The bad news

This course is only 8 weeks long.

- 9 theory lectures

- 3 expert/applied lectures

- 1 Q&A session

Note: this course is considered as hard!

# The ugly news

The course is packed

Students come from many different backgrounds and experiences.

We are forced by UvA planning to split the practicals in 4 groups.

Each person is randomly assigned to a group.

If your group timeslot is not suitable, you can try and switch with someone yourself. As long as rooms are not overcrowded, I am fine.



# The good news

This course is here to teach you a lot.

We are all here to help you out.

Canvas, lectures, labs, tutorials...

# Overall schedule

				Math tutorial	Lab
1	44	Intro and Regression I	Regression II		Lab Intro
2	45	Classification I	Classification II	Math tutorial 1	Lab Assignment 1
3	46	Deep Learning I	Representing Images		Lab Assignment 2
4	47	Representing Text	Deep Learning II	Math tutorial 2 Peer feedback open questions	Kaggle-Project week 1
5	48	Setting up a ML system <i>Intro to Reinforcement Learning</i>	Recommender Systems		Kaggle-Project week 2
6	49	AI for industry and humanities	Autonomous driving	Math tutorial 3	Kaggle-Project week 3
7	50	Q&A			Kaggle-Project week 4
8	51	Exam			Poster/Demo Session

# Lab assignments

Three weekly assignment files.

Week 1 has no deliverable, serves as practice.

Deadlines week 2: **10-11-2019 23:59**. Week 3: **17-11-2019 23:59**.

Each week, an ipython notebook to be filled in, with automatic grading!

# Tutorials and open questions

Dive deeper into math of machine learning.

Questions partially covered in exam.

**Flipped classroom tutorials in week 2, 4, and 6. Come prepared.**

Open question assignment (exam practice) on Canvas (due in week 4).



# Final project

Task: Select the most corresponding reason why this statement is against common sense.

Statement: He put an elephant into the fridge.

A: An elephant is much bigger than a fridge. (correct)

B: Elephants are usually white while fridges are usually white.

C: An elephant cannot eat a fridge.

## Project 2: Common sense challenge



## Project 1: Food recognition challenge

*when she looks perfect*



## Project 3: Meme analysis challenge

Implement and improve your own full machine learning pipeline!  
Competition amongst groups of three (groups made on Canvas).

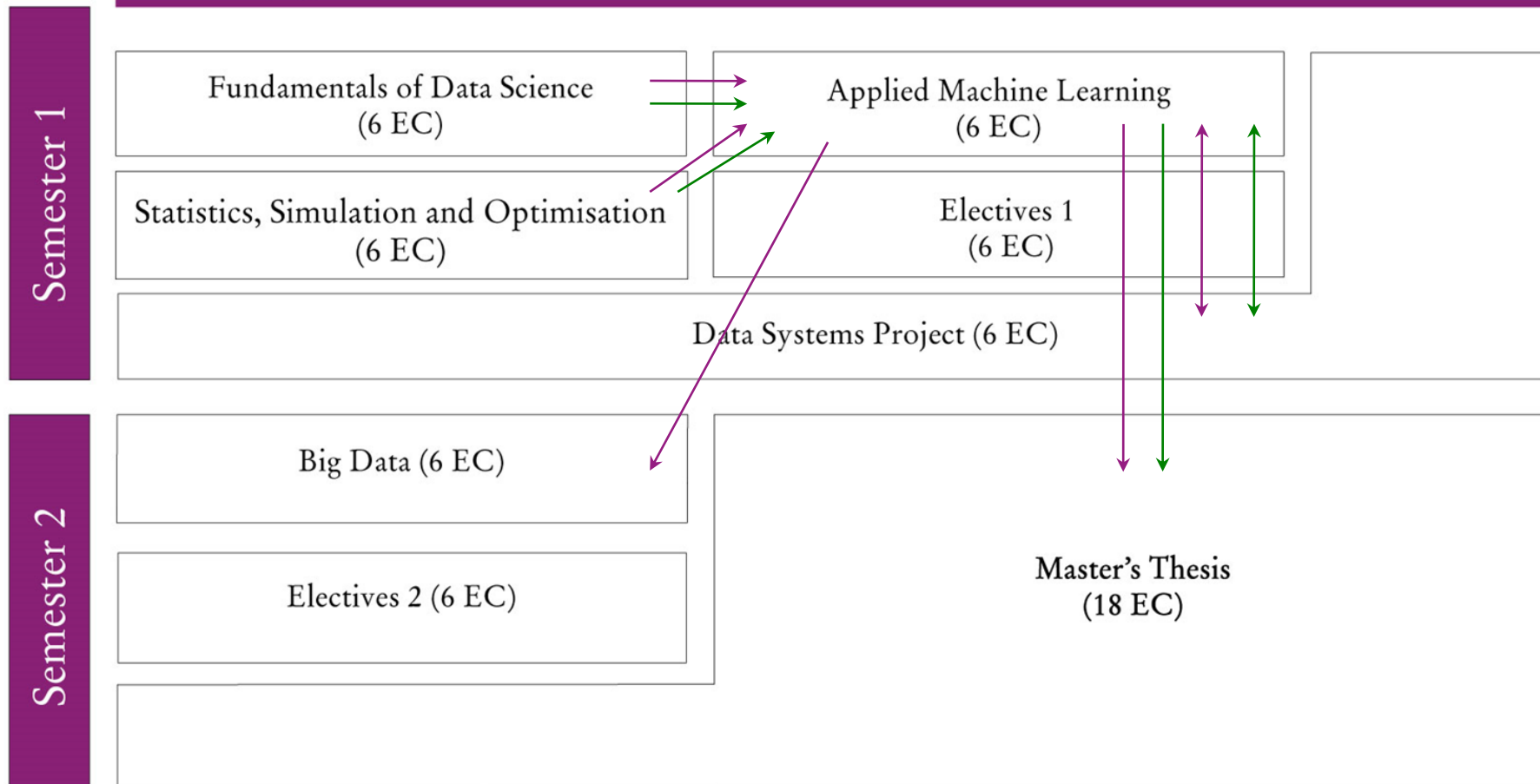
# Exam

Consists of closed and open questions.

Covers every lecture.

Examples from previous years on Canvas, naturally without answers.

## Study programme MSc Information Studies - Data Science (full-time)



→ Content

→ Skill

# Asking questions

For general questions and discussions, we use Canvas and lectures.

Programming and math questions discussed during labs and tutorials.

Questions on grades, groups, etc, mail Cristian:  
[c.m.rodriquezrivero@uva.nl](mailto:c.m.rodriquezrivero@uva.nl)

Any remaining problem or issues, weekly open office with Pascal:  
*Every Tuesday from 15:00 to 16:00 in C3.261.*



# Code of conduct

We encourage you to help each other...

Your grade depends on what you do, not what others do

... and us: give feedback on the course, it can always improve

High expectations

We from you, you from us

Come prepared: read materials, watch videos, look for solutions

Invest time

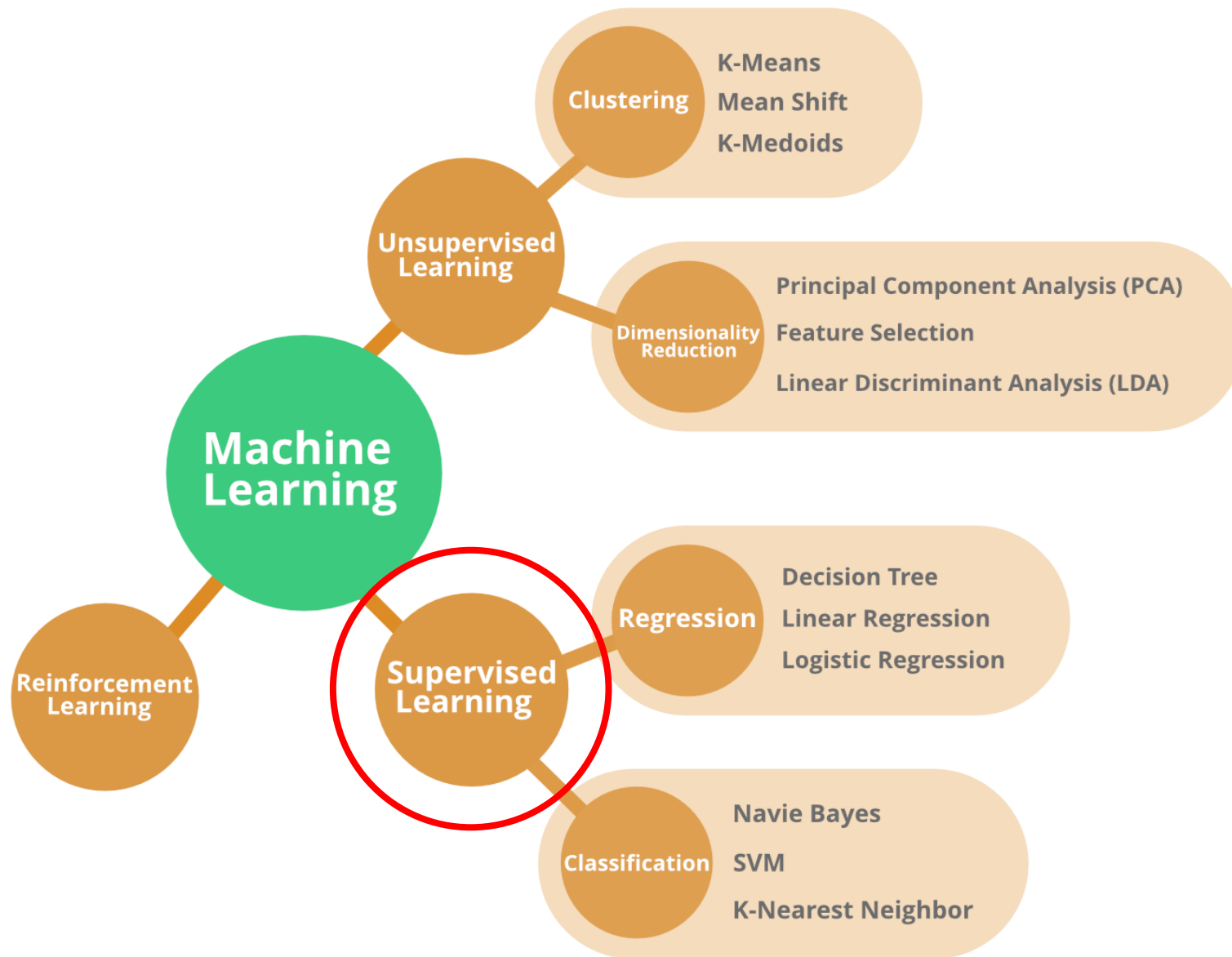
However, we do not tolerate blind copy

Not from each other

Not from the internet

# Applied Machine Learning

# Wat is machine learning to you?





# ARTIFICIAL INTELLIGENCE

Engineering of making Intelligent Machines and Programs



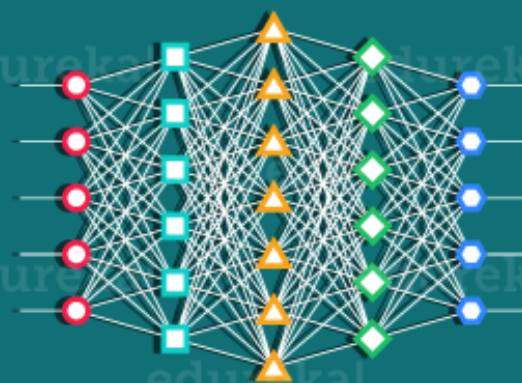
## MACHINE LEARNING

Ability to learn without being explicitly programmed



## DEEP LEARNING

Learning based on Deep Neural Network



1950's

1960's

1970's

1980's

1990's

2000's

2006's

2010's

2012's

2017's

# Machine learning 101

Given input  $\mathbf{x}$

Do some fancy computing

Predict output  $\mathbf{y}$

Tom Mitchel, Machine Learning, 1997:

*A computer learns, when*

*for some tasks  $T$ ; and*

*performance measure  $P$ ;*

*the value  $P$  increases for  $T$  with experience  $E$ .*

# Types of data

## **Structured**

Sensor readings, tax forms, excel tables

## **Unstructured**

Images, free text, speech

This course will especially focus on unstructured data!

# Machine learning lingo

## Concepts

Task, system, evaluation, data

## Mathematics

Required to formalize and understand the core

Functions, vectors, matrices, loss, probabilities, predictions

## Code

Enable and use machine learning

Python current go to, optionally with sklearn, PyTorch etc.

Source: Théo Szymkowiak, “12 sectors where automation will take over in the short term”

Machine learning has great impact potential across industries and use case types

Impact potential

Low  High

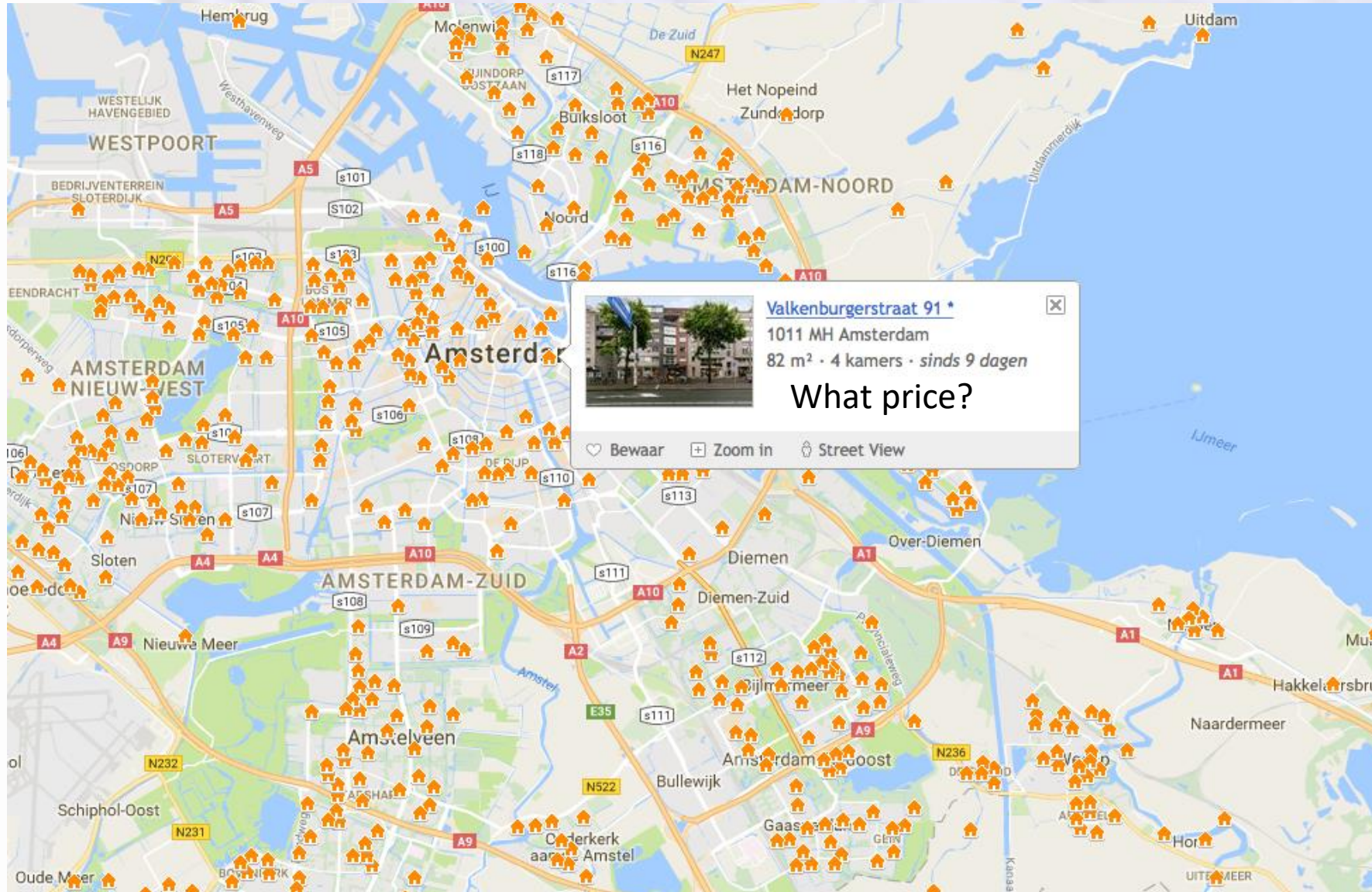
Problem type	Automotive	Manufacturing	Consumer	Finance	Agriculture	Energy	Health care	Pharmaceuticals	Public/social	Media	Telecom	Transport and logistics
Real-time optimization	High	High	High	Low	High	High	Low	Low	High	High	High	Low
Strategic optimization	High	High	High	High	High	High	High	High	High	High	High	Low
Predictive analytics	Low	High	High	High	High	High	High	High	High	High	High	High
Predictive maintenance	High	High	High	High	High	Low	Low	Low	High	Low	High	Low
Radical personalization	High	Low	High	High	High	Low	High	Low	High	Low	High	High
Discover new trends/anomalies	High	High	Low	High	Low	Low	High	High	Low	High	High	Low
Forecasting	High	High	High	High	High	High	High	High	High	Low	High	High
Process unstructured data	High	High	High	Low	High	Low	High	Low	Low	High	Low	High



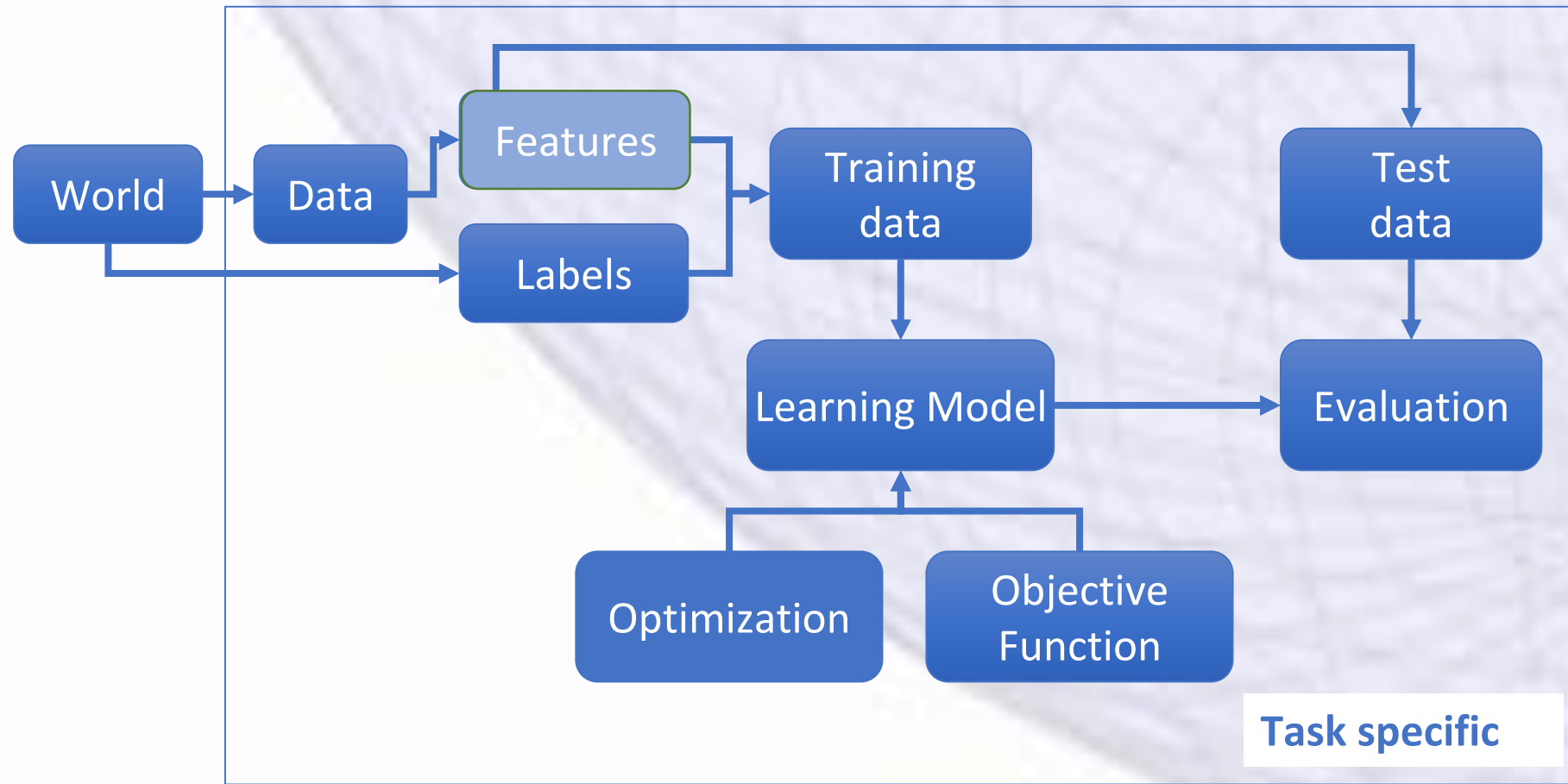
# Break

# Regression I

# Regression



# Machine learning system





# Input features

Represented as a vector  $\mathbf{x}$

Representation and values depend on task.

What is a possible feature vector of a house?

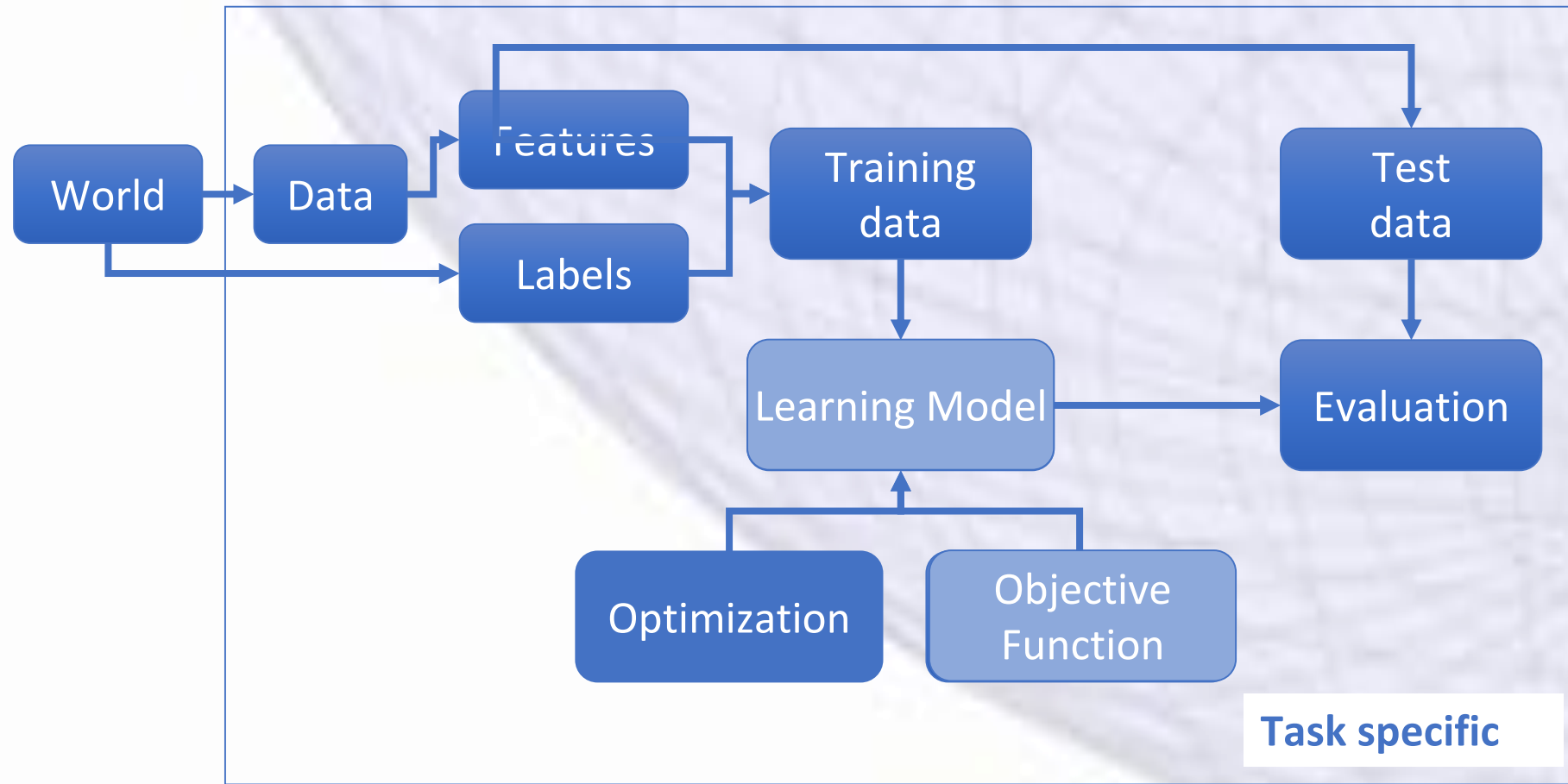
E.g. vector  $[m^2, \text{has\_garage}, \text{has\_balcony}, \text{nr\_bathrooms}, \dots]$

What is a possible feature vector of an image?

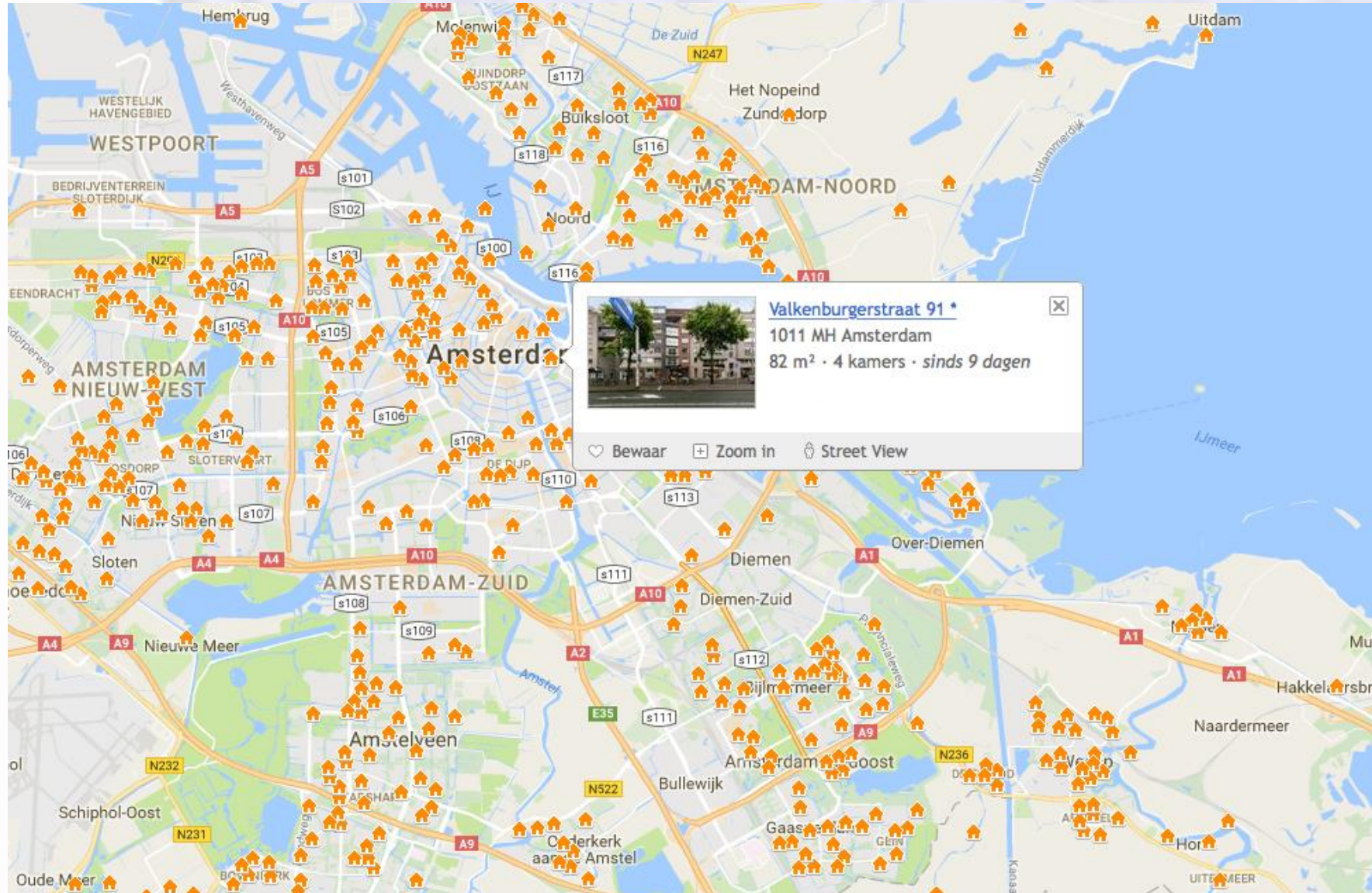
Hard to represent, topic of lecture 6!



# Machine learning system



# Estimating house price



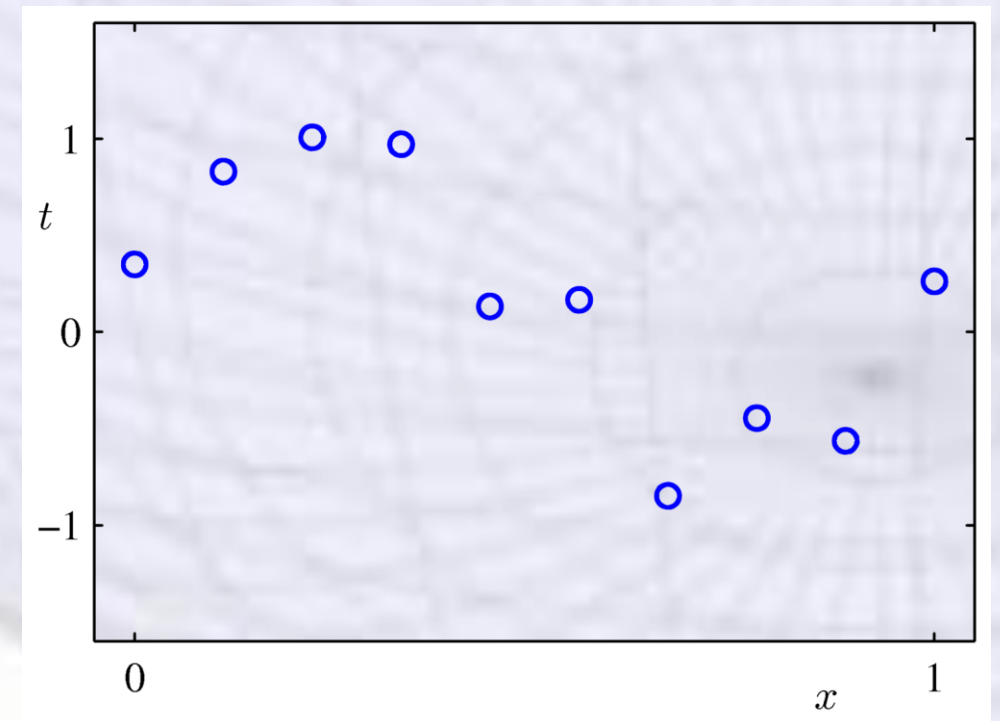
# Regression

Predict continuous output value  $t$  given input vector  $x$  (one value here).

$$t = f(x, w)$$

The goal is:

- Determine function class  $f$ .
- Find best values for  $w$  from training set.



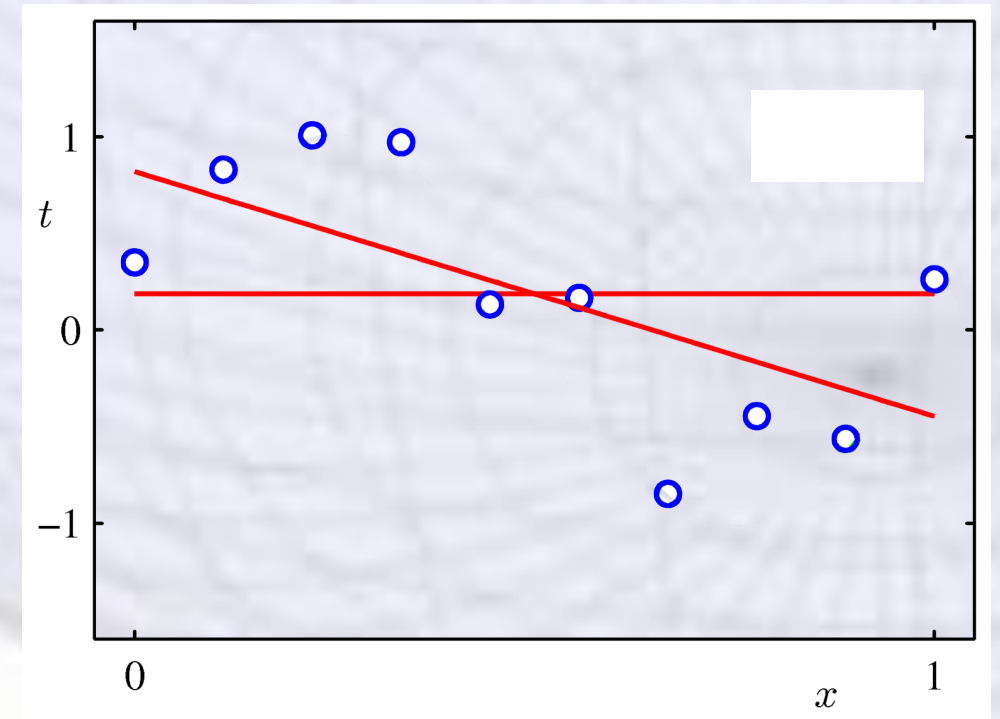


# Linear regression

Linear score function:

$$t = f(\mathbf{x}, \mathbf{w}) = \mathbf{x}^T \mathbf{w}$$

Number of parameters is equal to the number of features.



# Adding an intercept

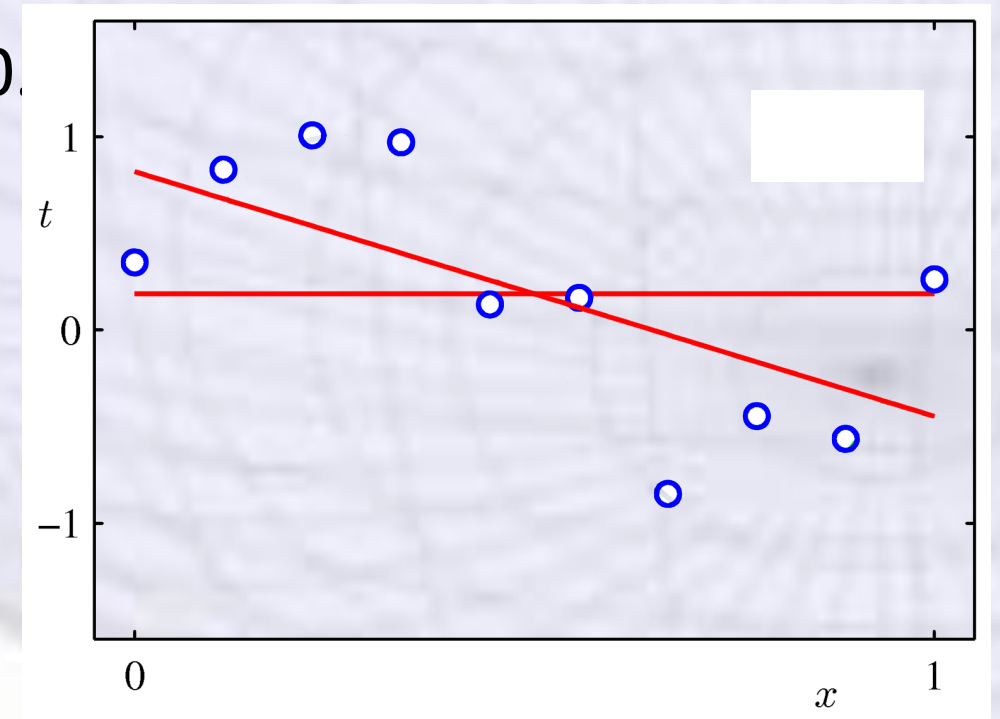
In a standard setup, the output is solely a function of the input.

If  $\mathbf{x} = [0,0,..,0]^T$  then the output is always 0.

To overcome this, we add an intercept:

$$\mathbf{x} := [\mathbf{x} \ 1]$$

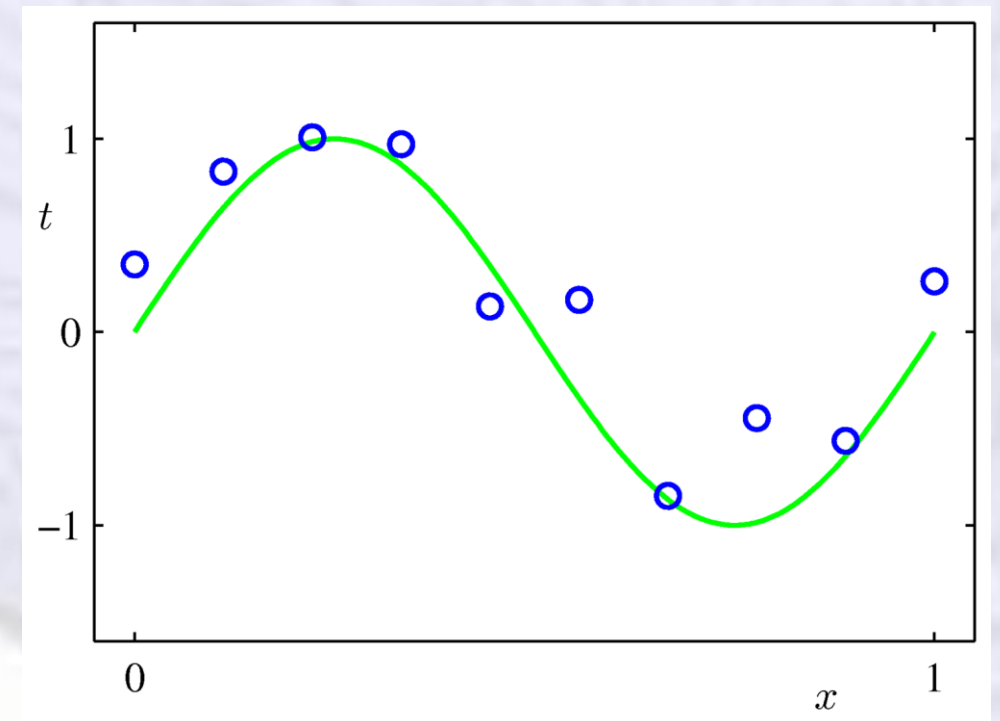
$$\mathbf{w} := [\mathbf{w} \ b]$$



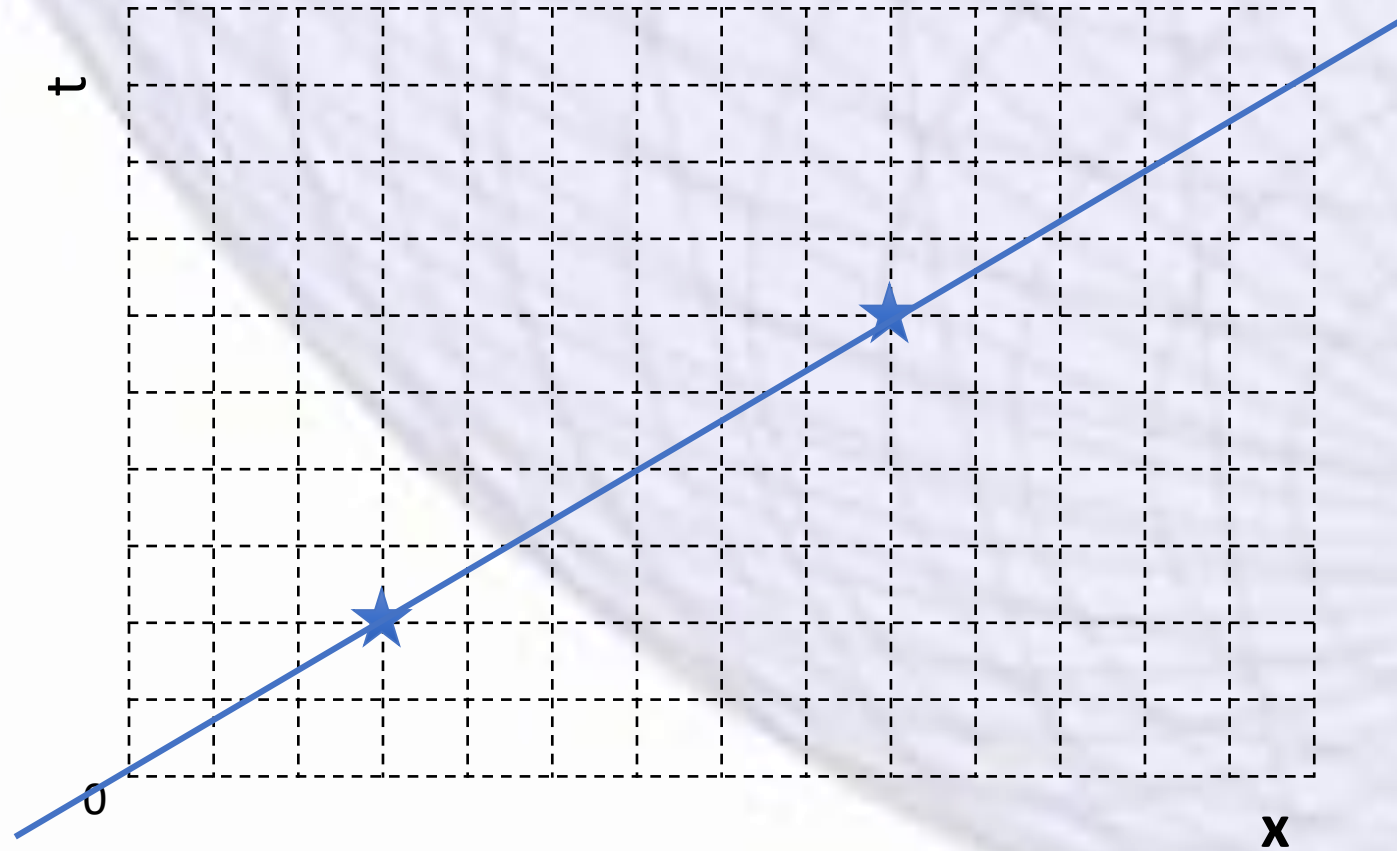


# Beyond linear regression

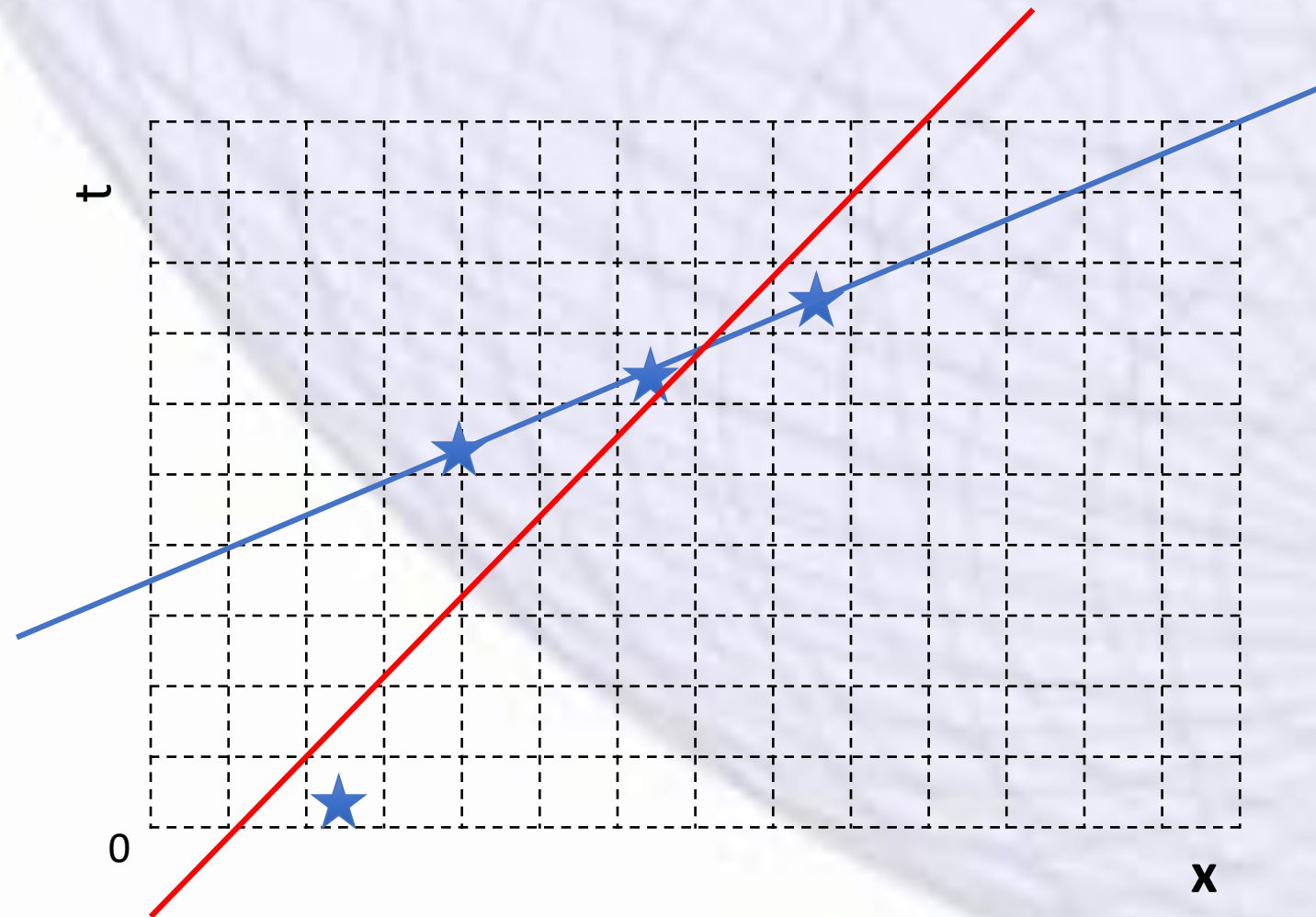
With the proper choice for  $f$ , we can do much more than straight lines.



# Fitting a line

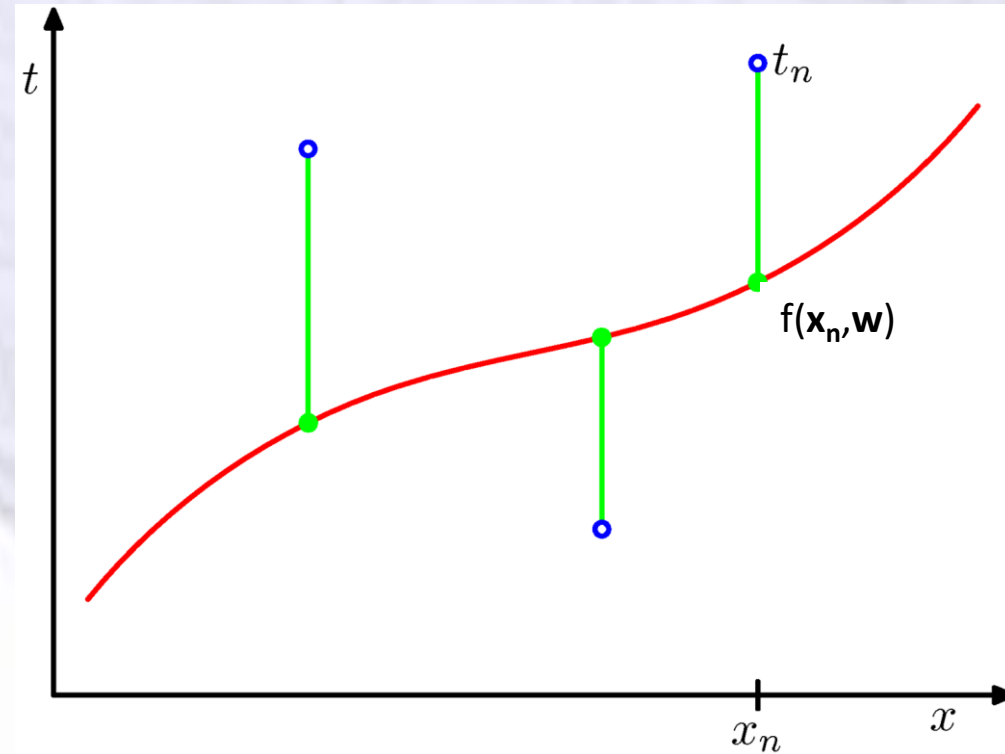


# Fitting a line



# When are predictions good?

Data point	$x_n$
True value	$t_n$
Predicted	$\hat{t}_n$



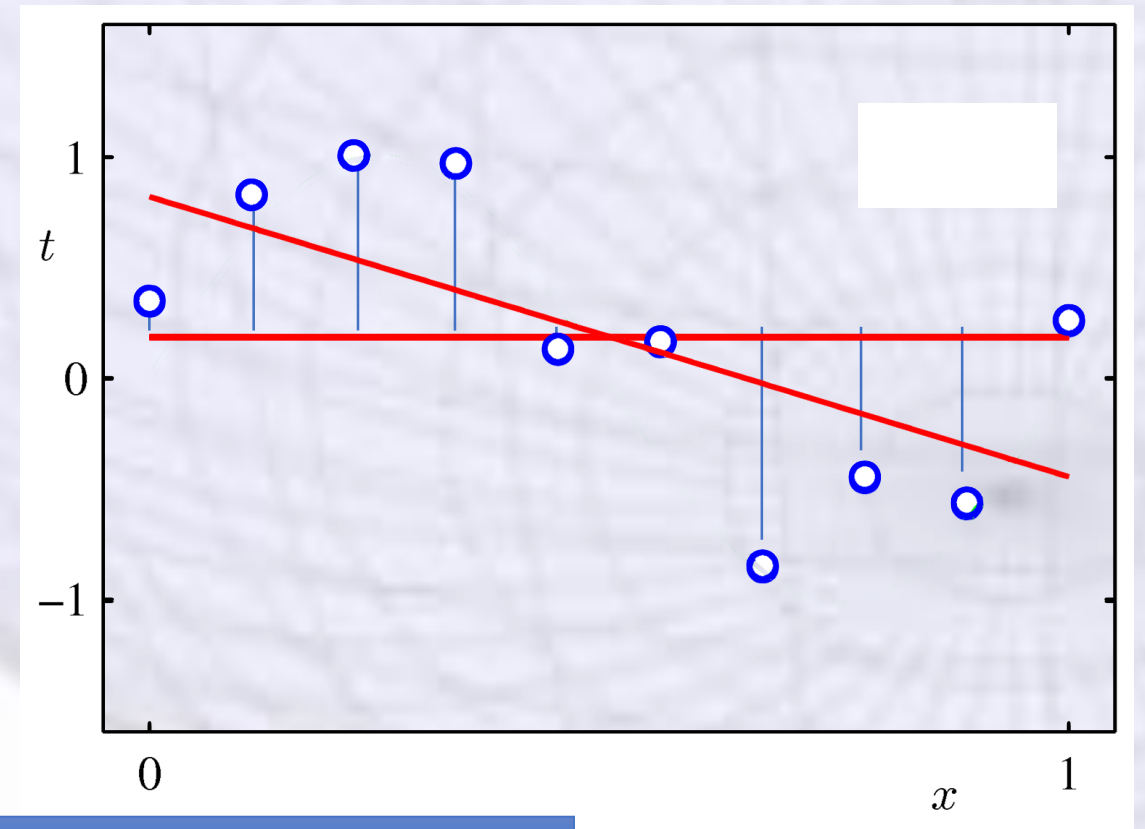
# How good is a model?

Loss function:  $(t_n - \hat{t}_n)^2$

Function:  $f(\mathbf{x}, \mathbf{w}) = \mathbf{x}^T \mathbf{w}$

Learning objective:

$$s(\mathbf{w}) = \frac{1}{2} \sum_n (t_n - \mathbf{x}_n^T \mathbf{w})^2$$

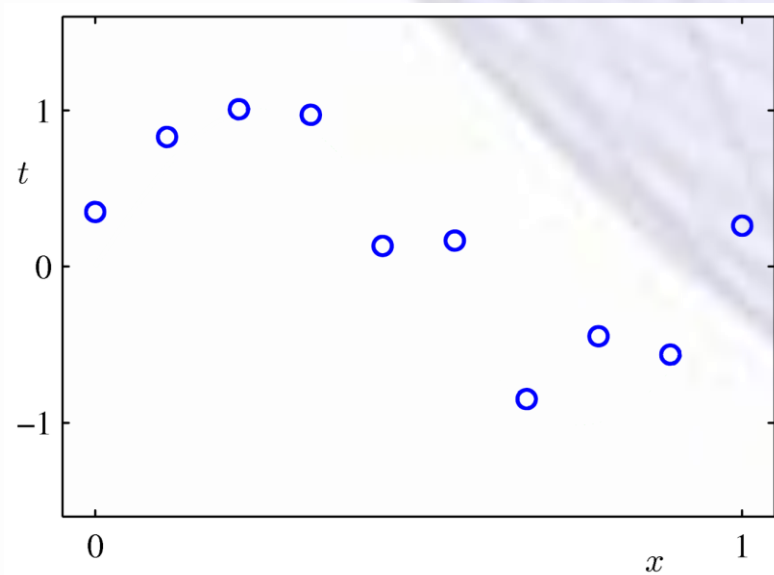


Each model is a line and corresponds to a score,  $s(\mathbf{w})$



# What if

I get more data?



I get more features?

$\mathbf{x} = [a, b, c, d, e, f]$

# Question: ZIP code feature

You want to add zip code as feature

New representation:  $x := [x \text{ zip}]$  (zip : 1098 ~~XH~~)

It is known by real estate agents that the zipcode is a strong feature, yet your new model performs badly.

1. Explain why this is the case
2. How could you do better?

# Content of today

Course logistics.

Machine learning definition and system.

Intro to regression.

# What is next

## **Laptopcollege**

Group D tomorrow, other groups on Friday.

## **Lecture**

Regression II, Friday 13:00-15:00, C1.110



# Thank you