

# Lecture 1 – Linear Regression

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# Outline

① Motivation

② Linear Regression I

③ Summary & Outlook

# Motivation

## Estimating House Prices!

- **Given:** You have access to actual house prices for, say, 1000 houses in Copenhagen that were recently sold.
- **Task:** Given a new house, estimate its price! That is, come up with an estimate in DKK! (You cannot try to sell this new house—this would give you a good estimate).



The screenshot shows the OpenStreetMap web application. At the top, there's a navigation bar with the OpenStreetMap logo, links for 'Edit', 'History', and 'Export', and a secondary bar with 'GPS Traces', 'User Diaries', 'Copyright', 'Help', 'About', 'Log In', and 'Sign Up'. Below the navigation bar is a search bar with the text 'Where is this?' and buttons for 'Go' and a location pin icon. The main area is a detailed street map of a neighborhood in Copenhagen, Denmark. The map shows a grid of streets with names like Nørsgade, Hallandsgade, Sverrigsgade, and others. Various landmarks are marked with icons, including the Amagerbro Apotek, Jacob Holms Minde, and the Frankrigshusene. The map also shows green spaces like Hundepark and Legeplads ved Fr.g. The interface includes navigation controls on the right side, such as a zoom in/out button, a full-screen button, and a compass. At the bottom left, there's a scale bar indicating 50 meters and 200 feet.

# Regression

- Given some data related to houses, estimate the price  $y \in \mathbb{R}$  in DKK for each house
- Given some stock, estimate the value  $y \in \mathbb{R}$  it will have in ten days
- Given the results of biopsy, demographics and disease history predict the survival time  $y \in \mathbb{R}$  of a patient

These tasks are called **regression tasks** since we are interested in a real value  $y \in \mathbb{R}$

# Classification

- Given some photos, classify them into “cats” ( $y = 0$ ), “dogs” ( $y = 1$ ), or “other” ( $y = 2$ )
- Given the results of biopsy, demographics and disease history predict the if the patient will survive 3-year threshold ( $y = 1$ ), or not ( $y = 0$ )

These tasks are called classification tasks since we are interested in a class  $y \in \{0, 1, 2, \dots\}$

# Clustering

- Given some photos, automatically partition them into groups
- Given the results of biopsy, demographics and disease partition patients into groups

Classes/groups not known beforehand. These tasks are called clustering tasks.

# Dimensionality reduction

- Reducing the database size by removing unnecessary data dimensions
- Simplify data interpretation



# Demo: Machine Learning & Scikit-Learn



Home Installation Documentation ▾ Examples

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Next

Plotting Cros...

**scikit-learn**  
**v0.19.1**

Other versions

Please **cite us**  
if you use the  
software.

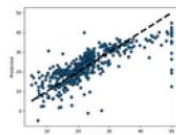
## Examples

General examples  
Examples based on  
real world datasets  
Biclustering  
Calibration  
Classification  
Clustering  
Covariance estimation  
Cross decomposition  
Dataset examples  
Decomposition  
Ensemble methods  
Tutorial exercises  
Feature Selection  
Gaussian Process for  
Machine Learning  
Generalized Linear  
Models  
Manifold learning  
Gaussian Mixture  
Models  
Model Selection  
Multitarget methods

## Examples

### General examples

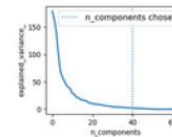
General-purpose and introductory examples for the scikit.



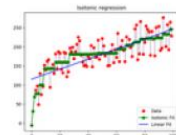
Plotting Cross-  
Validated  
Predictions



Concatenating  
multiple feature  
extraction



Pipelining:  
chaining a PCA  
and a logistic



Isotonic  
Regression



Imputing missing  
values before  
building an



Face completion  
with a multi-output  
estimators

[http://scikit-learn.org/stable/auto\\_examples/index.html](http://scikit-learn.org/stable/auto_examples/index.html)

Next

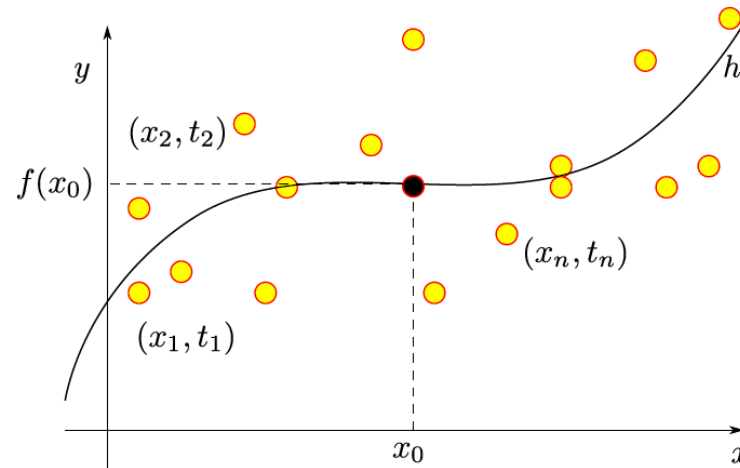
# Outline

① Motivation & Organization

② Linear Regression I

③ Summary & Outlook

# Regression



## A Learning Problem

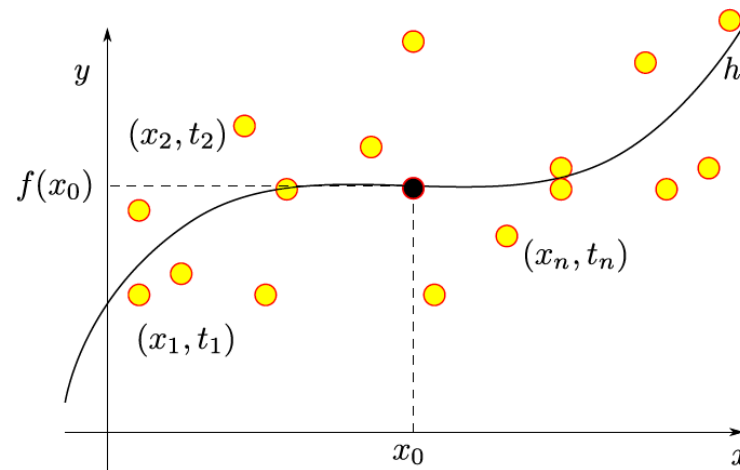
- **Input:**  $N$  pairs  $(\mathbf{x}_1, t_1), \dots, (\mathbf{x}_N, t_N)$  of observed
  - ▶ input variables/vectors  $\mathbf{x}_n \in \mathbb{R}^D$  and
  - ▶ target variables  $t_n \in \mathbb{R}$ .

- **Assumption:** There is a functional relationship

$$y = f(\mathbf{x}),$$

where  $f: \mathbb{R}^D \rightarrow \mathbb{R}$ .

# Regression



## A Learning Problem

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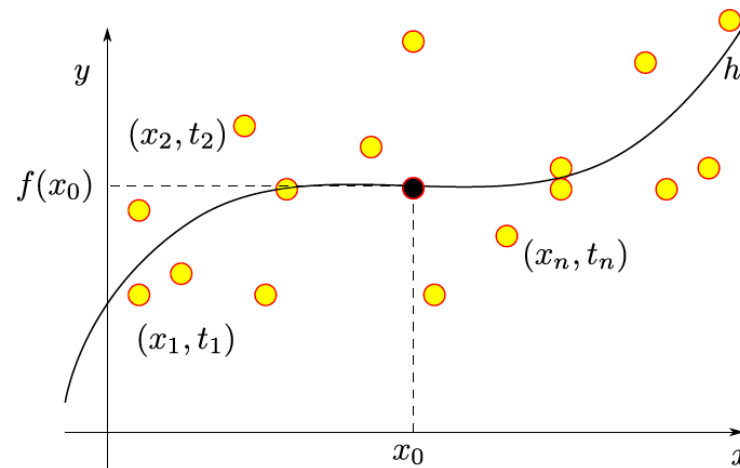
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- **Goal:** Learn the function  $f(\mathbf{x})$  from the  $N$  data points!

# Regression



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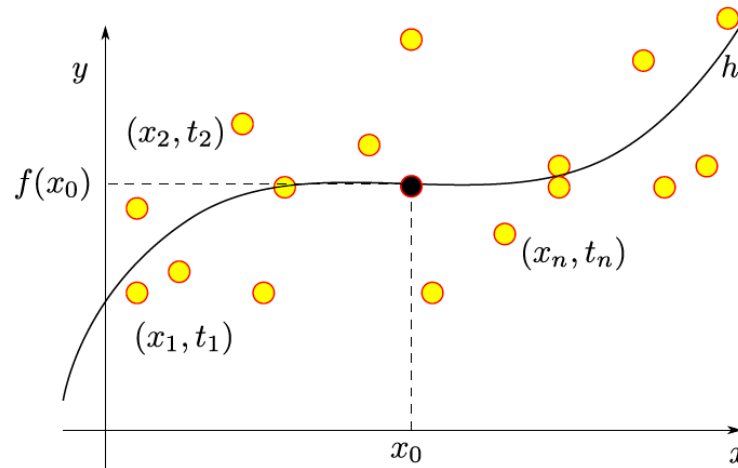
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- **What is this good for?**



# Regression



## A Learning Problem

- **Input:**  $N$  pairs  $(\mathbf{x}_1, t_1), \dots, (\mathbf{x}_N, t_N)$  of observed
  - ▶ input variables/vectors  $\mathbf{x}_n \in \mathbb{R}^D$  and
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- **Assumption:** There is a functional relationship

$$y = f(\mathbf{x}),$$

where  $f: \mathbb{R}^D \rightarrow \mathbb{R}$ .

- **Goal:** Learn the function  $f(\mathbf{x})$  from the  $N$  data points!
- **What is this good for?** Given a new observed input variable  $\mathbf{x}_0$ , we can “predict” the corresponding output variable  $f(\mathbf{x}_0)$ !

# Example: murder rates

- Unemployment rates  $\rightarrow$  murder rates
- Question: What are the  $\mathbf{x}_n$  and  $t_n$ ?

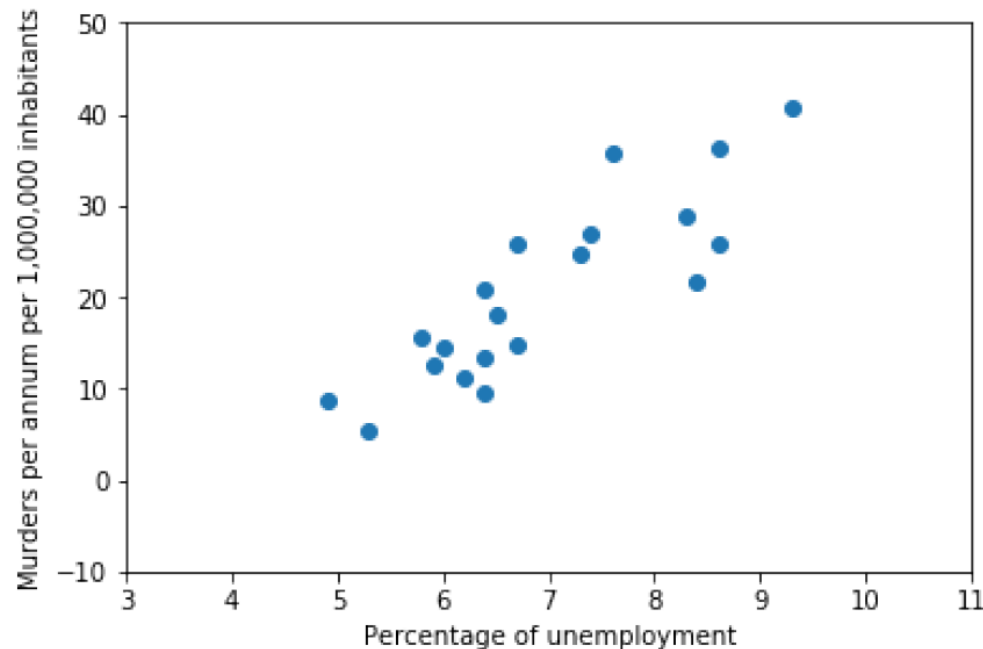
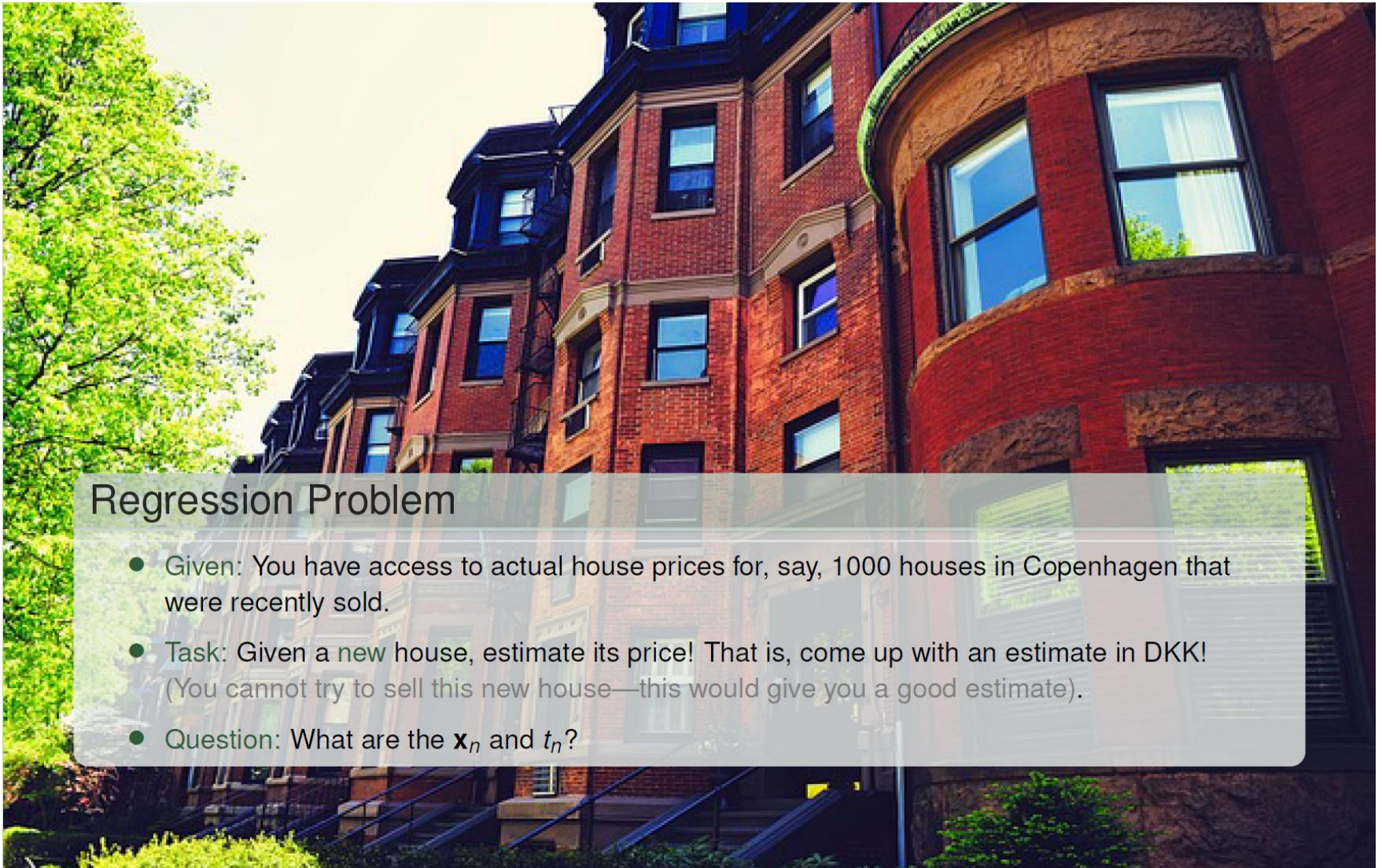


Figure: Murder rates versus unemployment rates in an American city<sup>1</sup>

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<sup>1</sup> Helmut Spaeth, Mathematical Algorithms for Linear Regression, Academic Press, 1991, ISBN 0-12-656460-4; D G Kleinbaum and L L Kupper, Applied Regression Analysis and Other Multivariable Methods, Duxbury Press, 1978, page 150; <http://people.sc.fsu.edu/~jburkardt/datasets/regression>

# Example: house price



## Regression Problem

- **Given:** You have access to actual house prices for, say, 1000 houses in Copenhagen that were recently sold.
- **Task:** Given a **new** house, estimate its price! That is, come up with an estimate in DKK! (You cannot try to sell this new house—this would give you a good estimate).
- **Question:** What are the  $\mathbf{x}_n$  and  $t_n$ ?

# Notation: vectors

- Let's say that our data is defined with  $D$  features. So one data sample  $\mathbf{x}$  will look like:

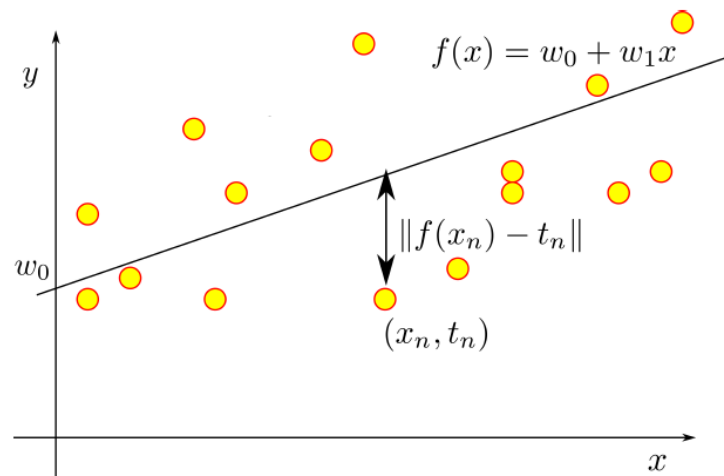
$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_D \end{bmatrix}$$

- That's annoying to type, so we will write  $\mathbf{x} = [x_1, x_2, \dots, x_D]^T$

# Linear regression: single feature data

- Let us start with  $D = 1$ , i.e., with input data of the form  $x_n \in \mathbb{R}$ .
- Let us consider models  $f$  of the form

$$f(x) = f(x; w_0, w_1) = w_0 + w_1 x$$

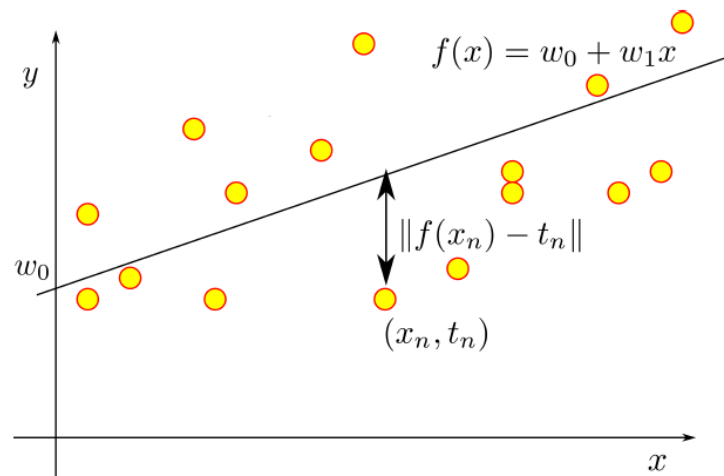




# Linear regression: single feature data

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- Comment: If we set  $\mathbf{x} = [1, x]^T$  and  $\mathbf{w} = [w_0, w_1]^T$ , then we have:

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

# Example: murder rates

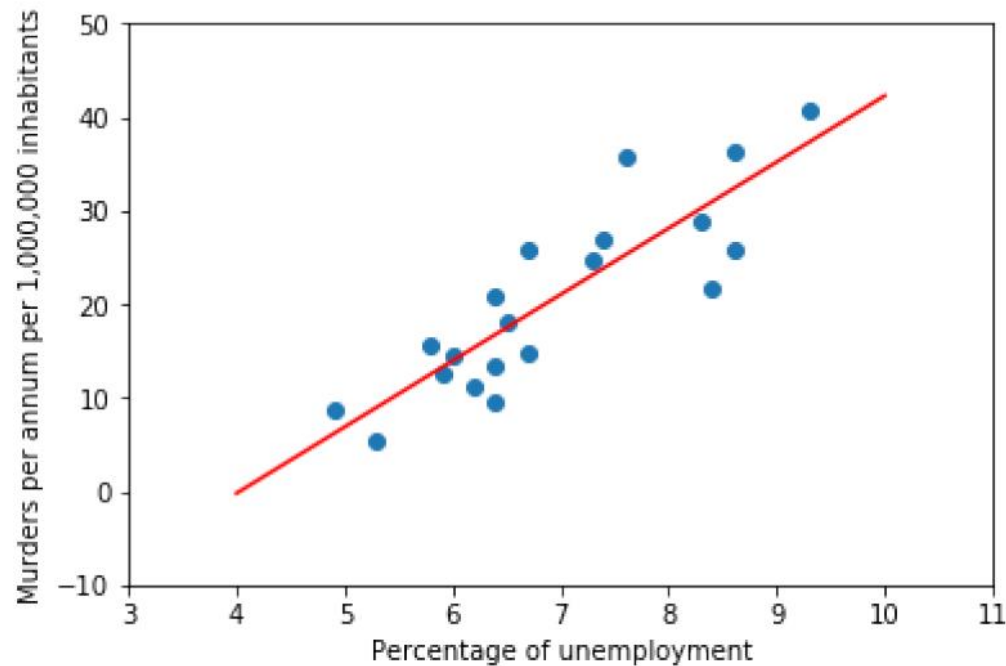


Figure: What is a “good” model? How can we measure its “quality”?

# Performance evaluation

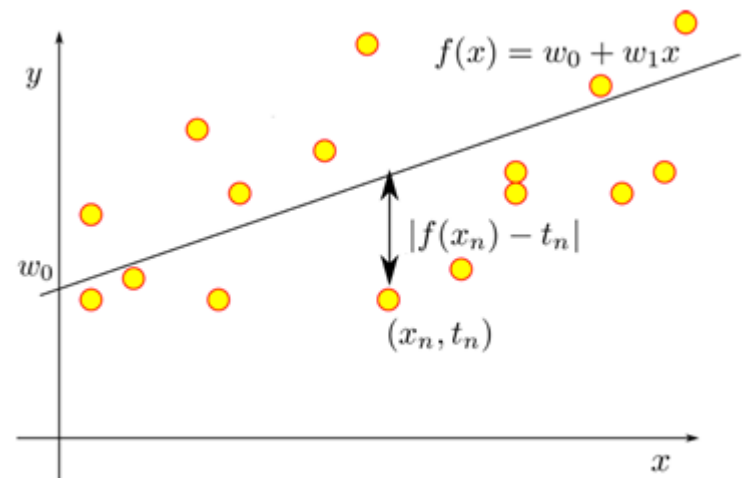
**Regression:** Labels are floating/integer numbers

- Mean absolute error

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

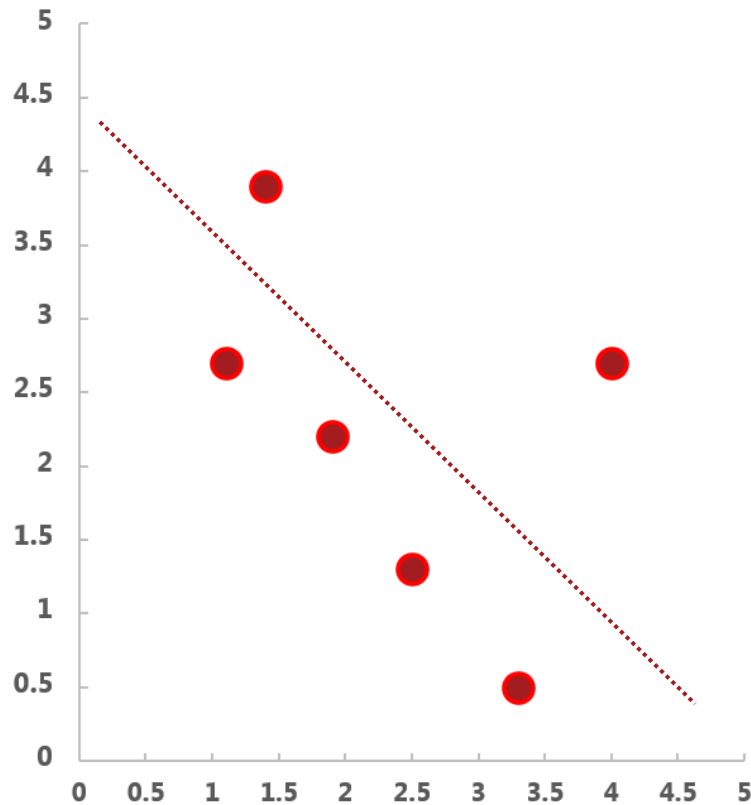
- Mean squared error

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

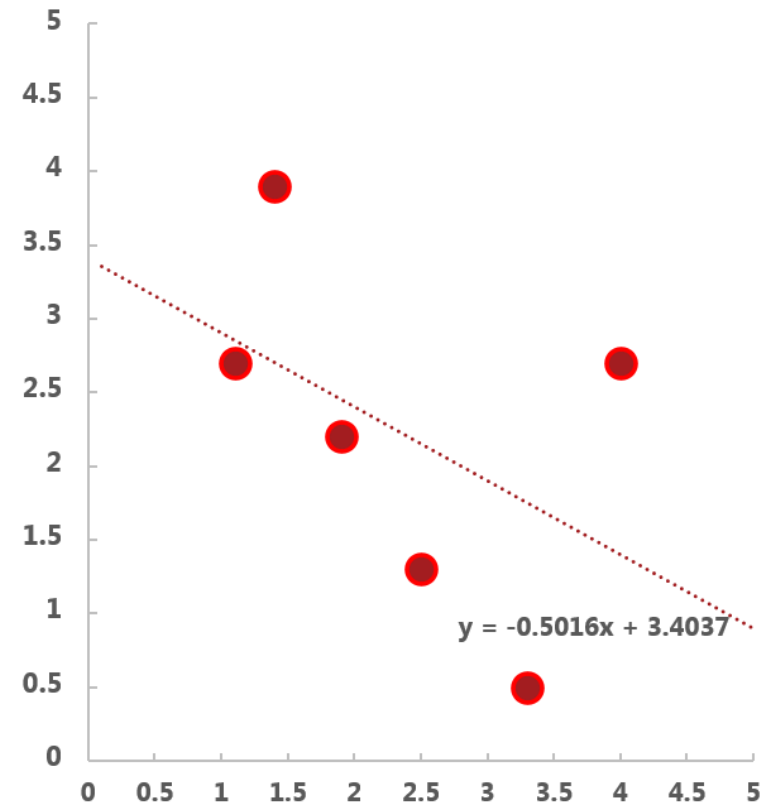


# Performance evaluation

## Which loss function to choose?



**MAE, or L1 loss**



**MSE, or L2 loss**

# The square loss function

- We would like to minimize the “error” made when using  $f$  to predict values  $f(x) = w_0 + w_1 x$  on the given data. One possible choice for such an error function is the square loss function

$$(f(x_n; w_0, w_1) - t_n)^2,$$

which measures the discrepancy between a target  $t_n$  and the associated predicted value  $f(x_n; w_0, w_1)$ .

- We aim at a low loss for all the data points, i.e.:

$$\mathcal{L} = \frac{1}{N} \sum_{n=1}^N (f(x_n; w_0, w_1) - t_n)^2$$

- Goal: Find optimal parameters  $\hat{w}_0$  and  $\hat{w}_1$  that minimize this overall loss:

$$(\hat{w}_0, \hat{w}_1) = \operatorname{argmin}_{w_0, w_1} \frac{1}{N} \sum_{n=1}^N (f(x_n; w_0, w_1) - t_n)^2$$



# Computing the optimal parameters

$$\mathcal{L}(w_0, w_1) = \frac{1}{N} \sum_{n=1}^N (f(x_n; w_0, w_1) - t_n)^2 = \frac{1}{N} \sum_{n=1}^N ((w_0 + x_n w_1) - t_n)^2$$

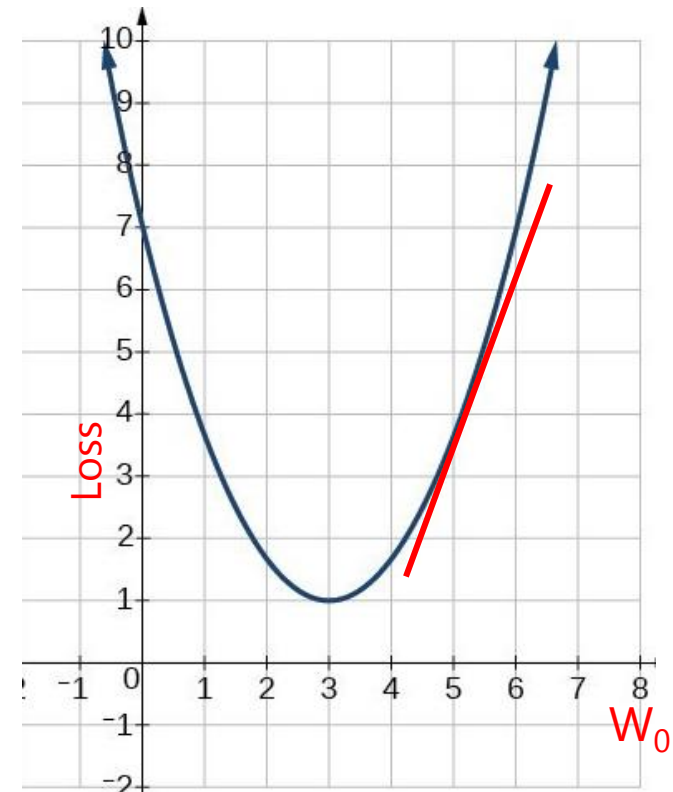
- We would like to find the two coefficients  $w_0$  and  $w_1$  that minimize the above objective! **Question:** How can we find these coefficients?

# Iterative optimization: derivatives

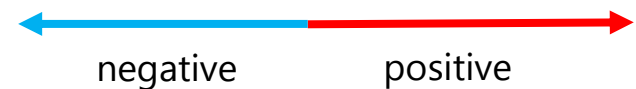
We want the loss to be as small as possible, i.e. find its minimum.

We use derivatives to find minima/maxima of a function:

- How fast function changes
- Will it increase or decrease



derivatives are:



# Computing the optimal parameters

$$\mathcal{L}(w_0, w_1) = \frac{1}{N} \sum_{n=1}^N (f(x_n; w_0, w_1) - t_n)^2 = \frac{1}{N} \sum_{n=1}^N ((w_0 + x_n w_1) - t_n)^2$$

- We have a function with two variables  $w_0$  and  $w_1$  and are searching for vector  $\mathbf{w} = [w_0, w_1]^T$  corresponding to a minimum w.r.t.  $\mathcal{L}$ . Thus, the gradient of  $\mathcal{L}$  must vanish at  $\mathbf{w}$  (necessary condition!):

$$\nabla \mathcal{L}(w_0, w_1) = \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial w_0} \\ \frac{\partial \mathcal{L}}{\partial w_1} \end{bmatrix} \stackrel{!}{=} \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- Task: Compute both partial derivatives!

# Computing the optimal parameters

- One can simplify the objective as follows:

$$\begin{aligned}\mathcal{L}(w_0, w_1) &= \frac{1}{N} \sum_{n=1}^N ((w_0 + x_n w_1) - t_n)^2 \\ &= \frac{1}{N} \sum_{n=1}^N (w_0 + x_n w_1)^2 - 2(w_0 + x_n w_1)t_n + t_n^2 \\ &= \frac{1}{N} \sum_{n=1}^N w_0^2 + 2w_0 x_n w_1 + x_n^2 w_1^2 - 2w_0 t_n - 2x_n w_1 t_n + t_n^2\end{aligned}$$

- Hence, one directly obtains the partial derivatives:

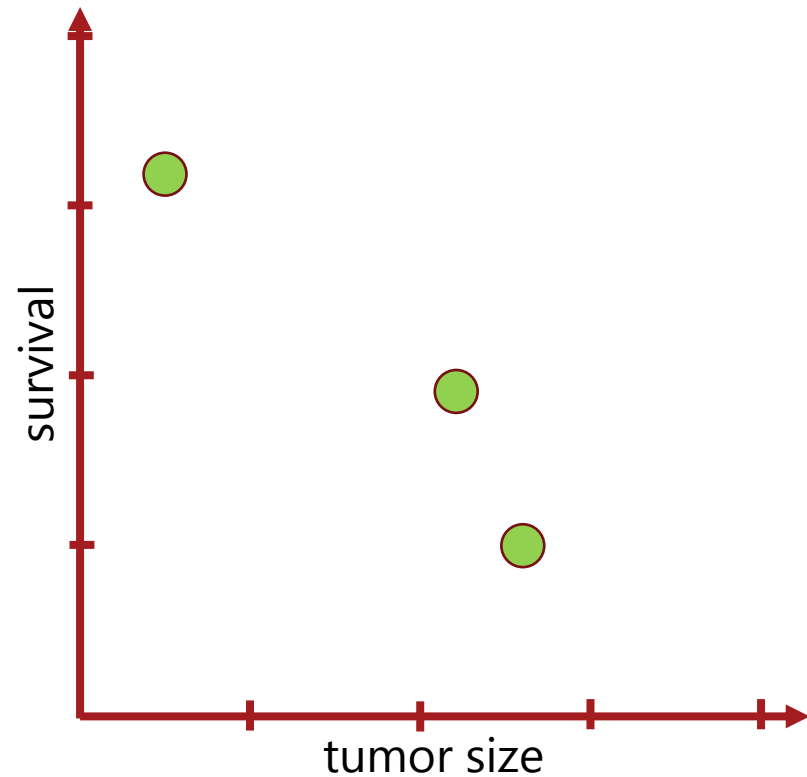
$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial w_0} &= 2w_0 + 2w_1 \frac{1}{N} \left( \sum_{n=1}^N x_n \right) - \frac{2}{N} \left( \sum_{n=1}^N t_n \right) \\ \frac{\partial \mathcal{L}}{\partial w_1} &= 2w_1 \frac{1}{N} \left( \sum_{n=1}^N x_n^2 \right) + \frac{2}{N} \left( \sum_{n=1}^N x_n (w_0 - t_n) \right)\end{aligned}$$

# Example

Patient survival depends on cancer size:

- Bigger tumors are worse
- Can we model this dependency?

	Tumor Size	Survival
Case1	0.5	3.2
Case2	2.3	1.9
Case3	2.9	1.0





# Example

	Tumor Size	Survival
Case1	0.5	3.2
Case2	2.3	1.9
Case3	2.9	1.0

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial w_0} &= 2w_0 + 2w_1 \frac{1}{N} \left( \sum_{n=1}^N x_n \right) - \frac{2}{N} \left( \sum_{n=1}^N t_n \right) \\ \frac{\partial \mathcal{L}}{\partial w_1} &= 2w_1 \frac{1}{N} \left( \sum_{n=1}^N x_n^2 \right) + \frac{2}{N} \left( \sum_{n=1}^N x_n (w_0 - t_n) \right)\end{aligned}$$

The derivative against  $w_0$ :

$$\begin{aligned}\frac{\partial L}{\partial w_0} &= 2w_0 + 2w_1 \frac{1}{3} (0.5 + 2.3 + 2.9) - \frac{2}{3} (3.2 + 1.9 + 1) \\ &= 2w_0 + 3.8w_1 + 4.07 = 0\end{aligned}$$

The derivative against  $w_1$ :

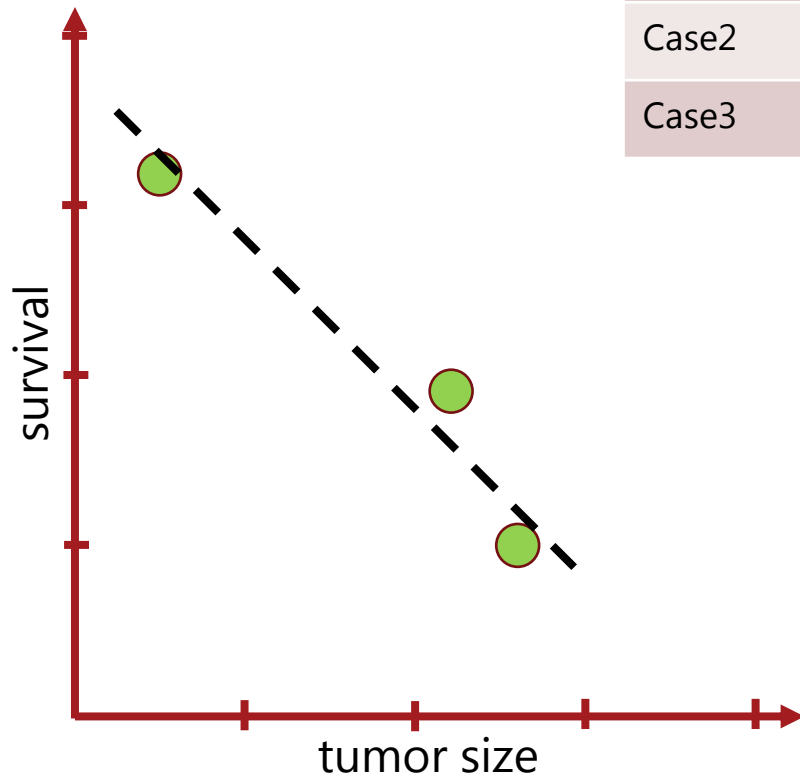
$$\begin{aligned}\frac{\partial L}{\partial w_1} &= 2w_1 \frac{1}{3} (0.25 + 5.29 + 8.41) + \frac{2}{3} 0.5(w_0 - 3.2) + \\ &\frac{2}{3} 2.3(w_0 - 1.9) + \frac{2}{3} 2.9(w_0 - 1) = 9.3w_1 + 3.8w_0 - 4.07 = 0\end{aligned}$$

$$w_0 = 3.69; w_1 = -0.87$$

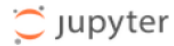
# Example

$$t = 3.69 - 0.87x$$

	Tumor Size	Survival	Predicted Survival
Case1	0.5	3.2	3.25
Case2	2.3	1.9	1.68
Case3	2.9	1.0	1.16



# Coding



Linear regression in one variable Last Checkpoint: 3 minutes ago (autosaved)



Logout

File Edit View Insert Cell Kernel Help

Trusted

Python 3



Import the usual libraries

```
In [1]: %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
```

We shall work with the dataset found in the file 'murderdata.txt', which is a 20 x 5 data matrix where the columns correspond to

Index (not for use in analysis)

Number of inhabitants

Percent with incomes below \$5000

Percent unemployed

Murders per annum per 1,000,000 inhabitants

**Reference:**

Helmut Spaeth, Mathematical Algorithms for Linear Regression, Academic Press, 1991, ISBN 0-12-656460-4.

D G Kleinbaum and L L Kupper, Applied Regression Analysis and Other Multivariable Methods, Duxbury Press, 1978, page 150.

<http://people.sc.fsu.edu/~jburkardt/datasets/regression>

**What to do?**

We start by loading the data; today we will study how the number of murders relates to the percentage of unemployment.

```
In [2]: data = np.loadtxt('murderdata.txt')
N, d = data.shape

unemployment = data[:,3]
murders = data[:,4]
```

# Coding

Jupyter Linear regression in one variable Last Checkpoint: 3 minutes ago (autosaved) Logout

File Edit View Insert Cell Kernel Help Trusted Python 3

Run Markdown

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Index (not for use in analysis)

## Coding Task

Compute the optimal coefficients:

- $\hat{w}_1 = \frac{\overline{xt} - \bar{x}\bar{t}}{\overline{x^2} - (\bar{x})^2}$

- $\hat{w}_0 = \bar{t} - \hat{w}_1 \bar{x}$

Make use of `np.dot` and `np.mean`. E.g., `np.dot(x, t) / N` computes  $\overline{xt}$ .

$$\bar{t} = \frac{1}{N} \sum_{n=1}^N t_n, \bar{x} = \frac{1}{N} \sum_{n=1}^N x_n, \overline{xt} = \frac{1}{N} \sum_{n=1}^N x_n t_n, \text{ and } \overline{x^2} = \frac{1}{N} \sum_{n=1}^N x_n^2$$

```
N, d = data.shape
```

```
unemployment = data[:,3]
murders = data[:,4]
```

# Questions?