

# **Linear Regression and Support Vector Machines**

**Marcus Rüb**

**Hahn-Schickard Villingen-Schwenningen  
Marcus.rueb@hahn-schickard.de**

# This session:

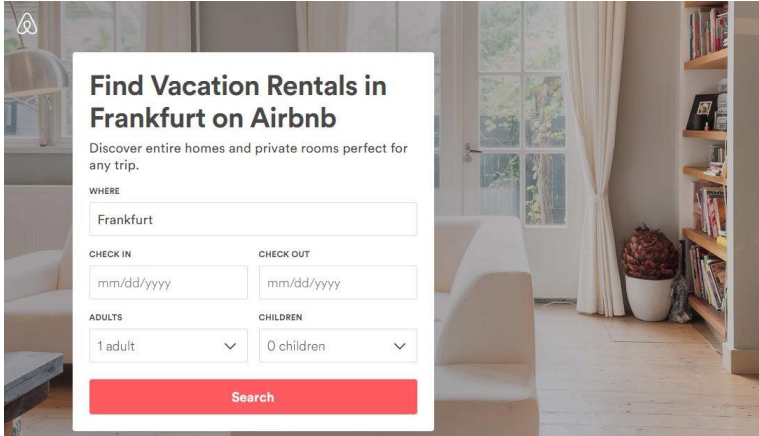
- **Linear regression**
- **Least square**
- **Gradient decent**
- **SVM**

# Outline for Supervised Learning (1)

## Supervised Learning (1)

- Linear, polynomial regression
- Lasso, Ridge, ElasticNet regression
- Logistic Regression
- Support Vector Machines (SVM)
  
- Hands-on Supervised Learning

Predict price of vacation rentals in Frankfurt on Airbnb

A screenshot of the Airbnb search interface overlaid on a background image of a modern living room. The search form is titled "Find Vacation Rentals in Frankfurt on Airbnb" and includes a subtext "Discover entire homes and private rooms perfect for any trip." The form fields are: "WHERE" with "Frankfurt" entered; "CHECK IN" and "CHECK OUT" both with placeholder text "mm/dd/yyyy"; "ADULTS" with a dropdown menu showing "1 adult"; and "CHILDREN" with a dropdown menu showing "0 children". A red "Search" button is at the bottom of the form.

**Find Vacation Rentals in Frankfurt on Airbnb**  
Discover entire homes and private rooms perfect for any trip.

WHERE  
Frankfurt

CHECK IN  
mm/dd/yyyy

CHECK OUT  
mm/dd/yyyy

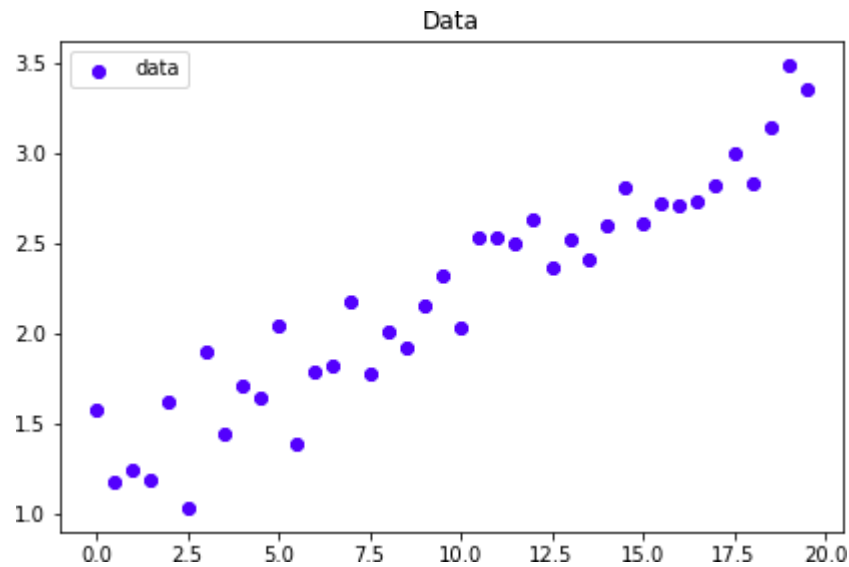
ADULTS  
1 adult

CHILDREN  
0 children

Search

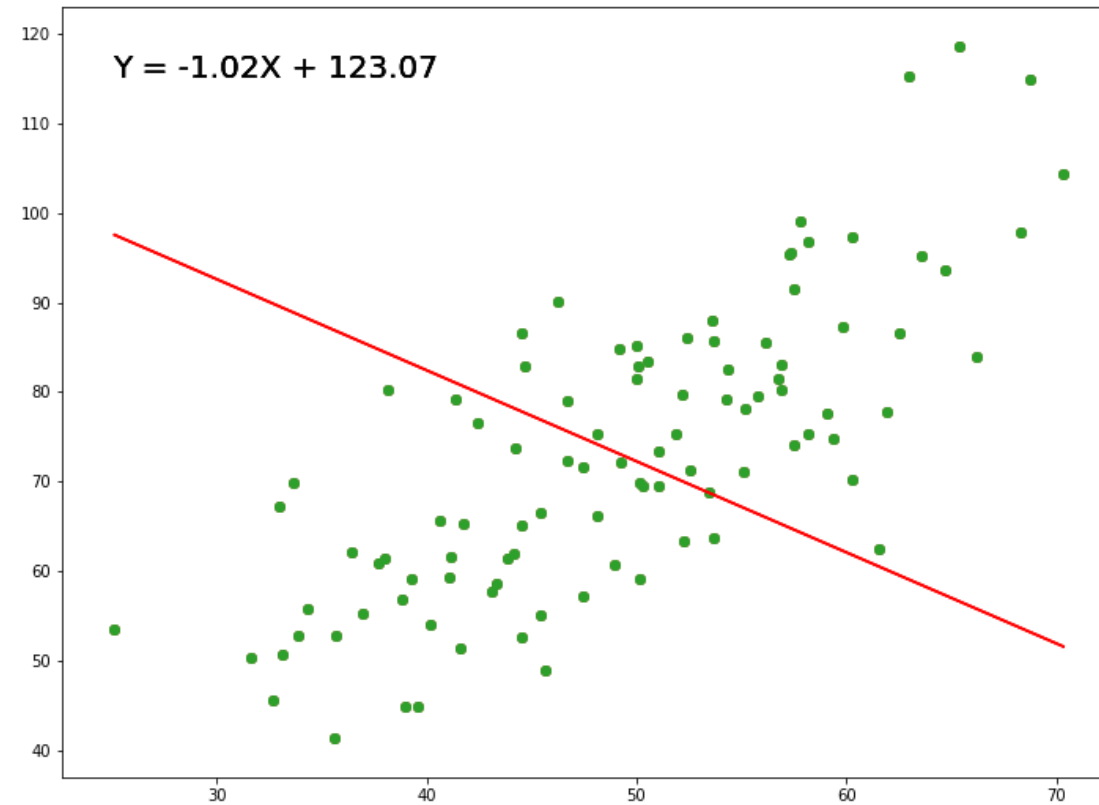
# Linear Regression

Let's create some data



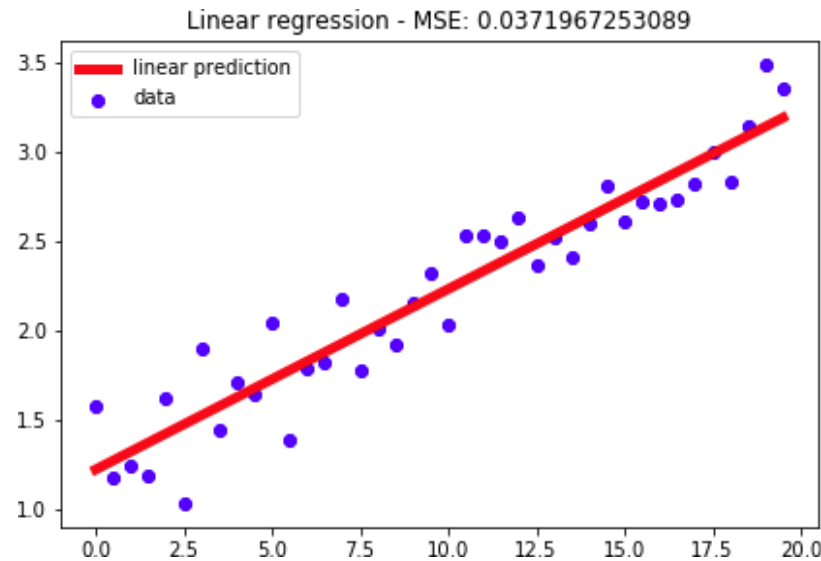
$$y = 0.1x + 1.25 + 0.2\text{GaussianNoise}$$

# Fit in a line



# Linear Regression

Let's perform linear regression...



$$y = 0.1x + 1.25 + 0.2 \text{ GaussianNoise}$$

$$y = mx + b$$

$w = 0.1014$   
 $b = 1.2258$

$$y = 0.1014x + 1.2258$$

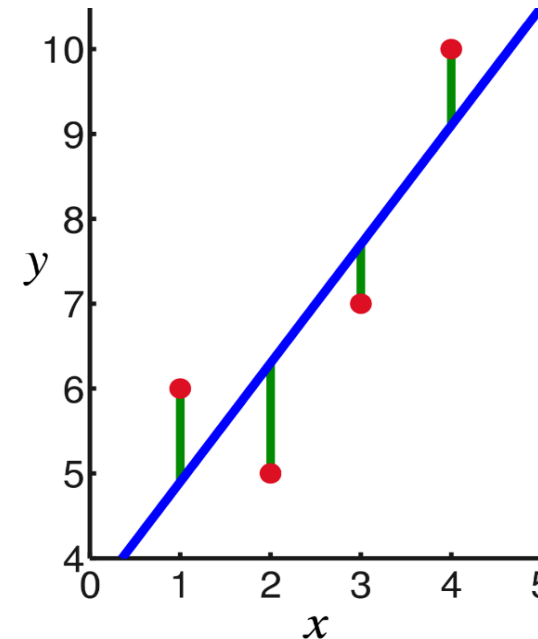
# How we fitted the line?

We just found the values of ' $m$ ' and ' $b$ ' that minimize the Mean Squared Error

$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2$$

where  $N$  is the number of data points,  
 $f_i$  the value returned by the model and  
 $y_i$  the actual value for data point  $i$ .

Mean Squared Error





Carl Friedrich Gauss

Born: 30. April 1777  
† 23. Februar 1855  
German mathematician

With 18 he invent the Least square method



# Least Square

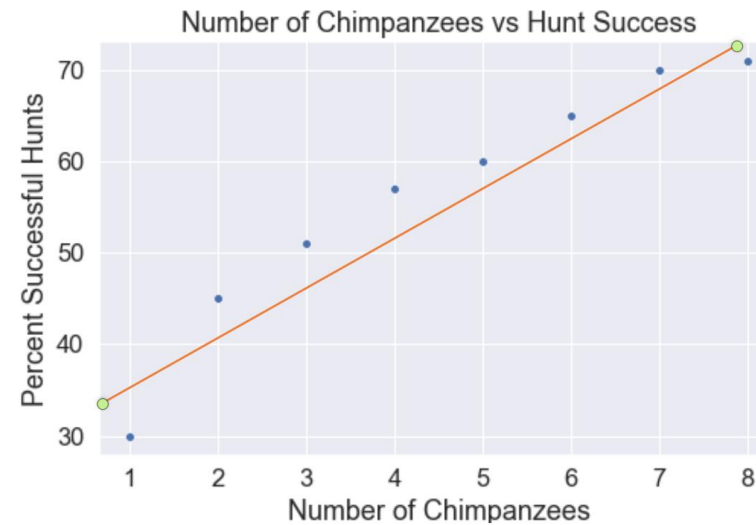
$$y = mx + b$$

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}$$

$$b = \frac{\sum y - m(\sum x)}{n}$$

Number of Chimpanzees	Percent Successful Hunts
0	1
1	2
2	3
3	4
4	5
5	6
6	7
7	8

n                      x                      y



Number of Chimpanzees (x)	Percent Successful Hunts (y)	xy	x <sup>2</sup>	y <sup>2</sup>
1	30	30	1	900
2	45	90	4	2025

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2} \quad b = \frac{\sum y - m(\sum x)}{n}$$

Number of Chimpanzees (x)	Percent Successful Hunts (y)	xy	x <sup>2</sup>	y <sup>2</sup>
1	30	30	1	900
2	45	90	4	2025
3	51	153	9	2601
4	57	228	16	3249
5	60	300	25	3600
6	65	390	36	4225
7	70	490	49	4900
8	71	568	64	5041
$\sum x$	$\sum y$	$\sum xy$	$\sum x^2$	$\sum y^2$
36	449	2249	204	26541

Number of Chimpanzees (x)	Percent Successful Hunts (y)	xy	x <sup>2</sup>	y <sup>2</sup>
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3	51	153	9	2601
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5	60	300	25	3600
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7	70	490	49	4900
8	71	568	64	5041
$\Sigma x$	$\Sigma y$	$\Sigma xy$	$\Sigma x^2$	$\Sigma y^2$
36	449	2249	204	26541

$$m = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{n(\Sigma x^2) - (\Sigma x)^2} \quad b = \frac{\Sigma y - m(\Sigma x)}{n}$$

$$m = \frac{8(2249) - (36)(449)}{8(204) - (36)^2} \quad b = \frac{449 - 5.4405(36)}{8}$$

$$m = 5.4405 \quad b = 31.6429$$

$$y = mx + b$$

$$y = 5.4405x + 31.6429$$

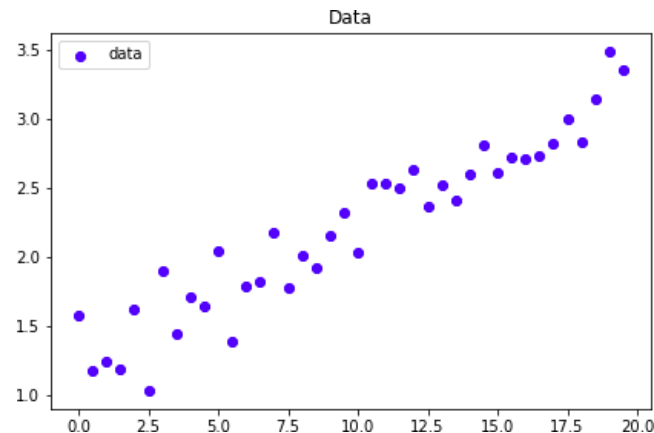
# Least Squares - notation

$$y = \underline{wx + b} = \underline{b + wx}$$

$$X = 1, x$$

$$W = b, w$$

$$y = WX = b + wx$$



Also called features

$$X = x_0, x_1, x_2, x_3, \dots, x_n \quad x_0 = 1$$

$$W = w_0, w_1, w_2, w_3, \dots, w_n \quad w_0 = b$$

$$y = WX = w_0x_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n$$

$x_0$	$x_1$	$y$
1	0.0	1.57
1	0.5	1.18
1	1.0	1.24
1	1.5	1.19
1	2.0	1.62

$X$  = matrix (m,n)

$Y$  = vector (m)

m = number of samples

n = number of features

# How we fitted the line?

Which values of line parameters minimize the Mean Squared Error?

## Least squares Method



Carl Friedrich Gauss

## Least Squares Method

$$\hat{W} = (X^T X)^{-1} X^T y$$

$$X = x_0, x_1, x_2, x_3, \dots, x_n \quad x_0 = 1$$

$$W = w_0, w_1, w_2, w_3, \dots, w_n \quad w_0 = b$$

$$y = WX = w_0 x_0 + w_1 x_1 + w_2 x_2 + \dots + w_n x_n$$

$\hat{W}$  is the best approximation to  $W$

# How we fitted the line?

Which values of line parameters minimize the Mean Squared Error?

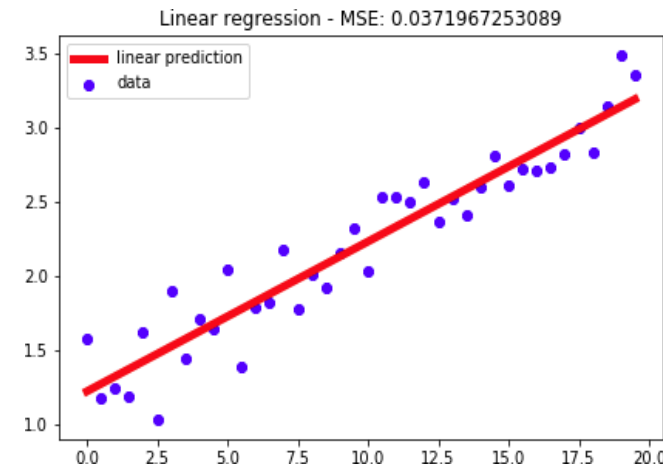
## Least squares Method



Carl Friedrich Gauss

## Least Squares Method

$$\hat{w} = (X^T X)^{-1} X^T y$$



$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2$$

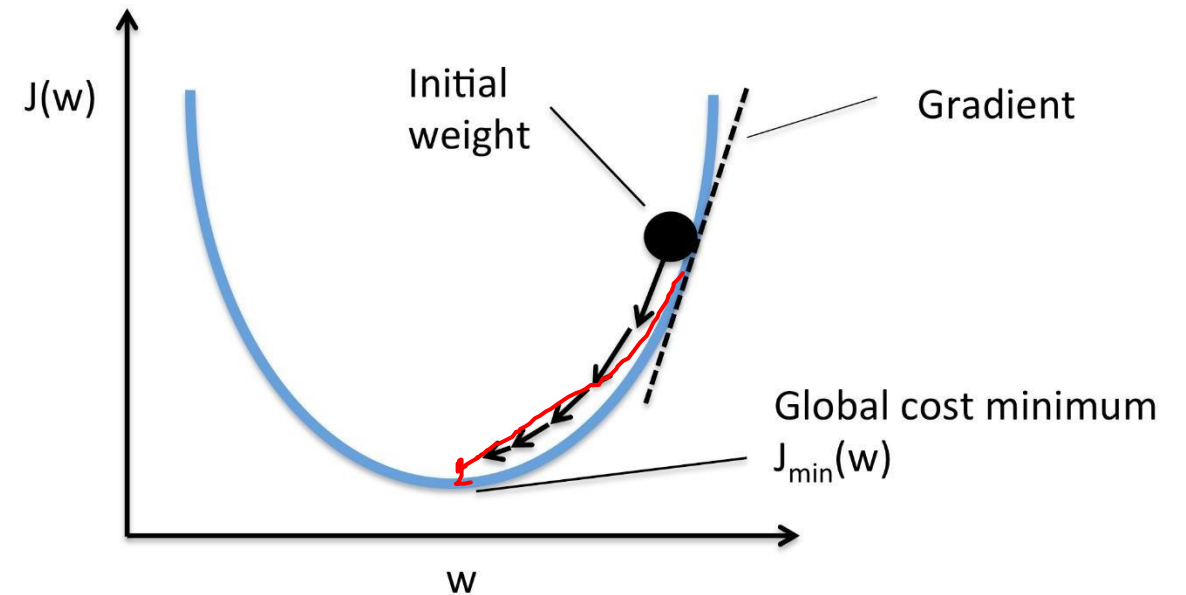
where  $N$  is the number of data points,  
 $f_i$  the value returned by the model and  
 $y_i$  the actual value for data point  $i$ .

Mean Squared Error

Learning

$$W = W - \alpha \frac{\partial J}{\partial W}$$

There is another way: Gradient Descent



Gradient Descent Visualization. Credit: [rasbt.github.io](https://github.com/rasbt)



# Gradient Descent

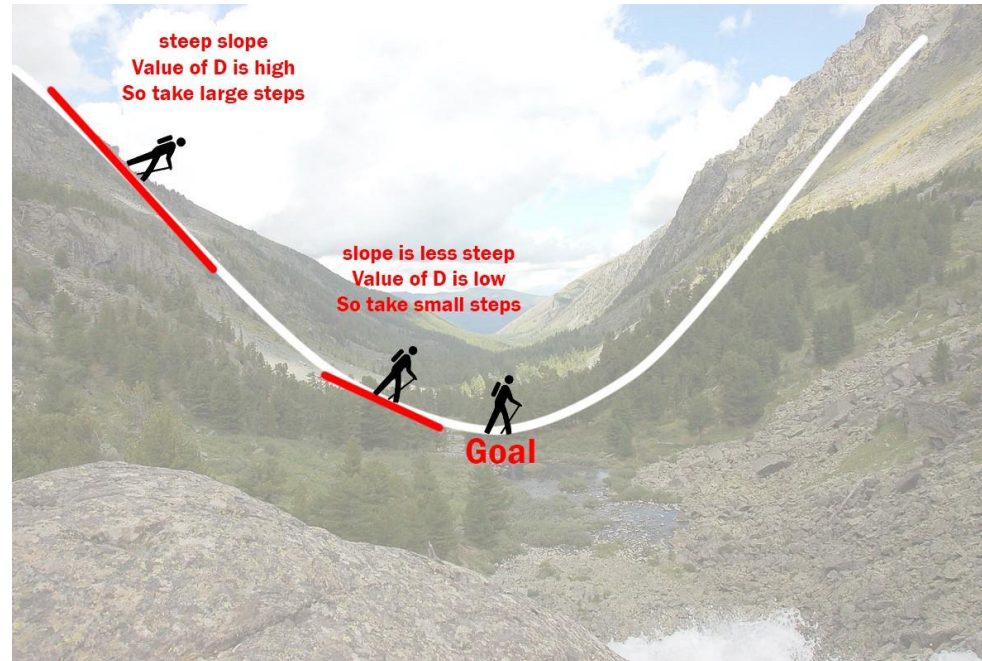
$$E = \frac{1}{n} \sum_{i=0}^n (y_i - \bar{y}_i)^2$$

↙

$$y = mx + b$$

↘

$$E = \frac{1}{n} \sum_{i=0}^n (y_i - (mx_i + c))^2$$



Derivation:

$$D_m = \frac{1}{n} \sum_{i=0}^n 2(y_i - (mx_i + c))(-x_i)$$

$$D_m = \frac{-2}{n} \sum_{i=0}^n x_i (y_i - \bar{y}_i)$$

$$D_c = \frac{-2}{n} \sum_{i=0}^n (y_i - \bar{y}_i)$$

$$m = m - \underline{L} \times D_m$$

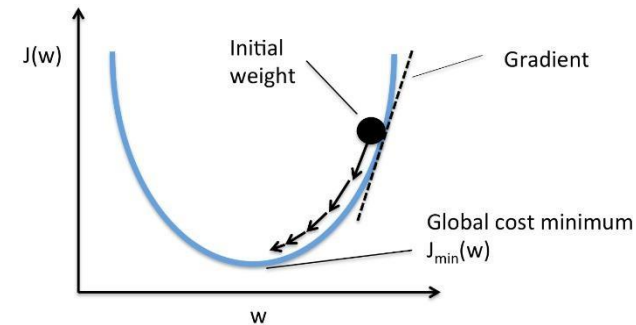
$$c = c - L \times D_c$$



$$\hat{w} = (X^T X)^{-1} X^T y$$

## Least Squares

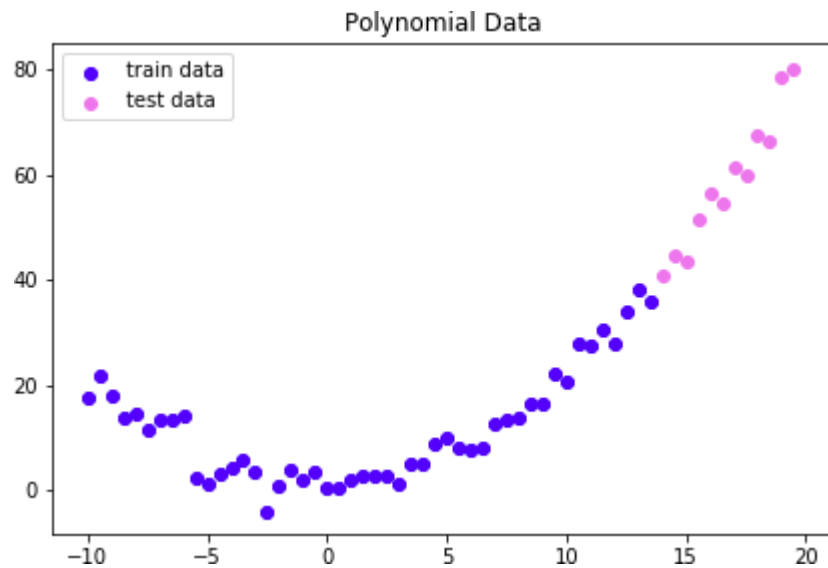
- when there is a relatively small number of features (< 1,000)



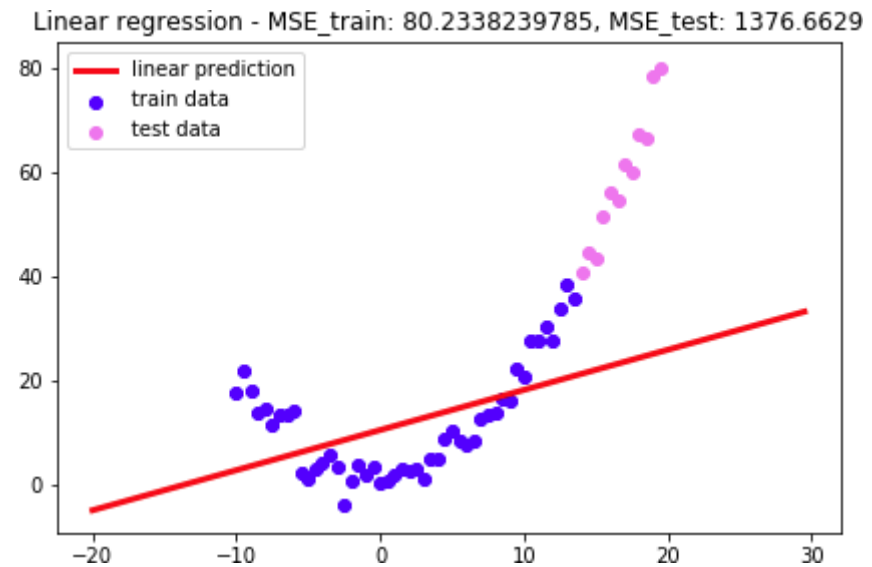
## Gradient Descent

- when there are many features (> 1,000)
- when we need to stop training at any time
  - e.g. if we only have 1 minute
- If data does not fit in memory
- If you have new data (e.g. stream) and don't want to start all over (with all previous data)

# Polynomial Regression



$$y = 0.2x^2 + 0.1x + 1 + 3\text{GaussianNoise}$$



$$\text{Linear Regression: } y = w_0 + w_1x$$

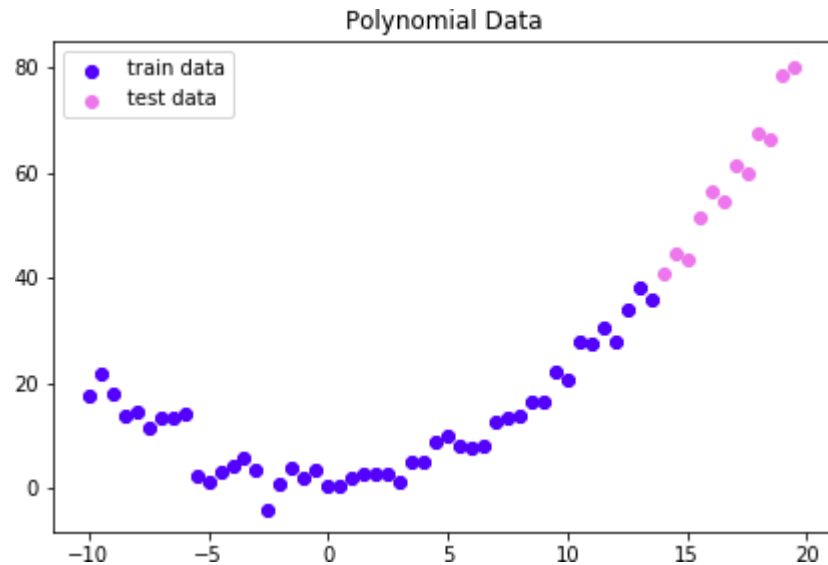
- You already know how to do it
- It is not a new technique, it's a **feature**

x		
$x_0$	$x_1$	$y$
1	-10.0	17.74
1	-9.5	21.86
1	-9	17.84
1	-8.5	13.71
1	-8	14.47

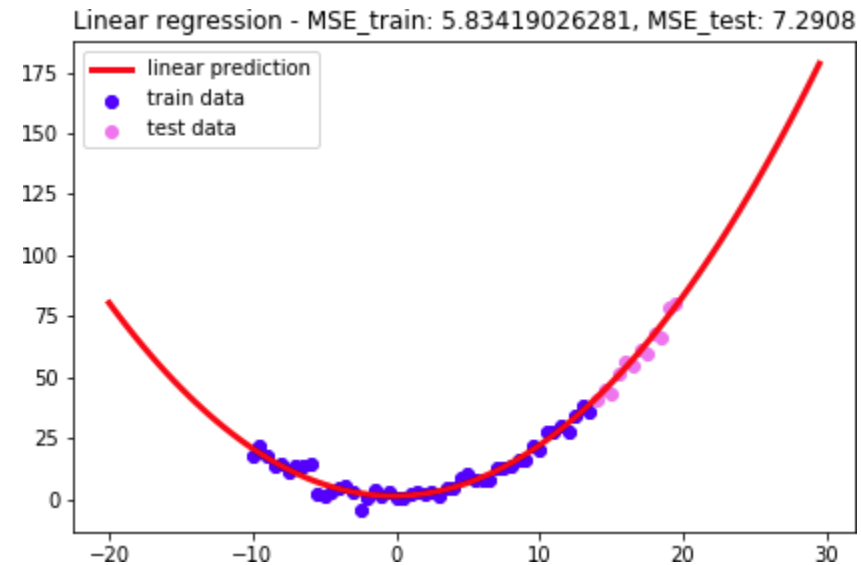


x		$x^2$	$y$
$x_0$	$x_1$	$x_2$	
1	-10.0	100.0	17.74
1	-9.5	90.25	21.86
1	-9	81.00	17.84
1	-8.5	72.25	13.71
1	-8	64.00	14.47

# Polynomial Regression



$$y = 0.2x^2 + 0.1x + 1 + 3\text{GaussianNoise}$$



$$\text{Linear Regression: } y = w_0 + w_1x + w_2x^2$$

- Polynomial Regression = Linear Regression with polynomial features
- You can get creative:
  - $x^2, x^3, x^4, \dots$
  - $zx^2, zx^3, z^2x^2, \dots$

Features	$x$		$x^2$	$y$
	$x_0$	$x_1$	$x_2$	
	1	-10.0	100.0	17.74
	1	-9.5	90.25	21.86
	1	-9	81.00	17.84
	1	-8.5	72.25	13.71
	1	-8	64.00	14.47

# What if some of the inputs are irrelevant?

- Ridge Regression
- Lasso Regression
- ElasticNet Regression

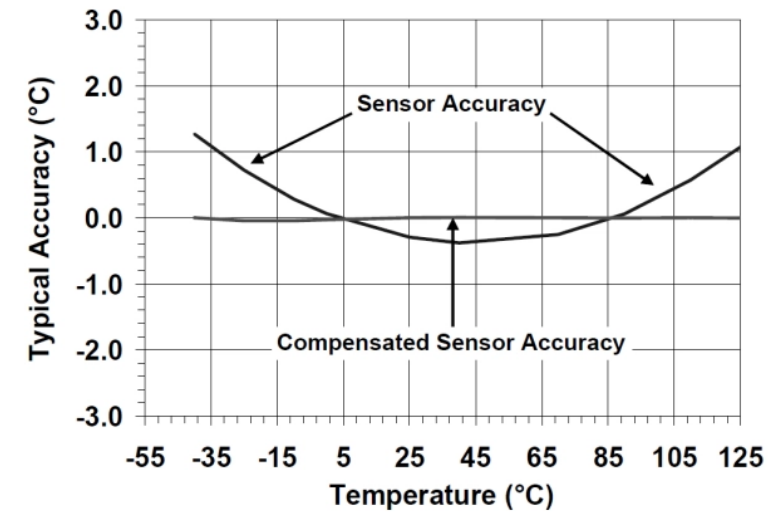


# Where is this used?

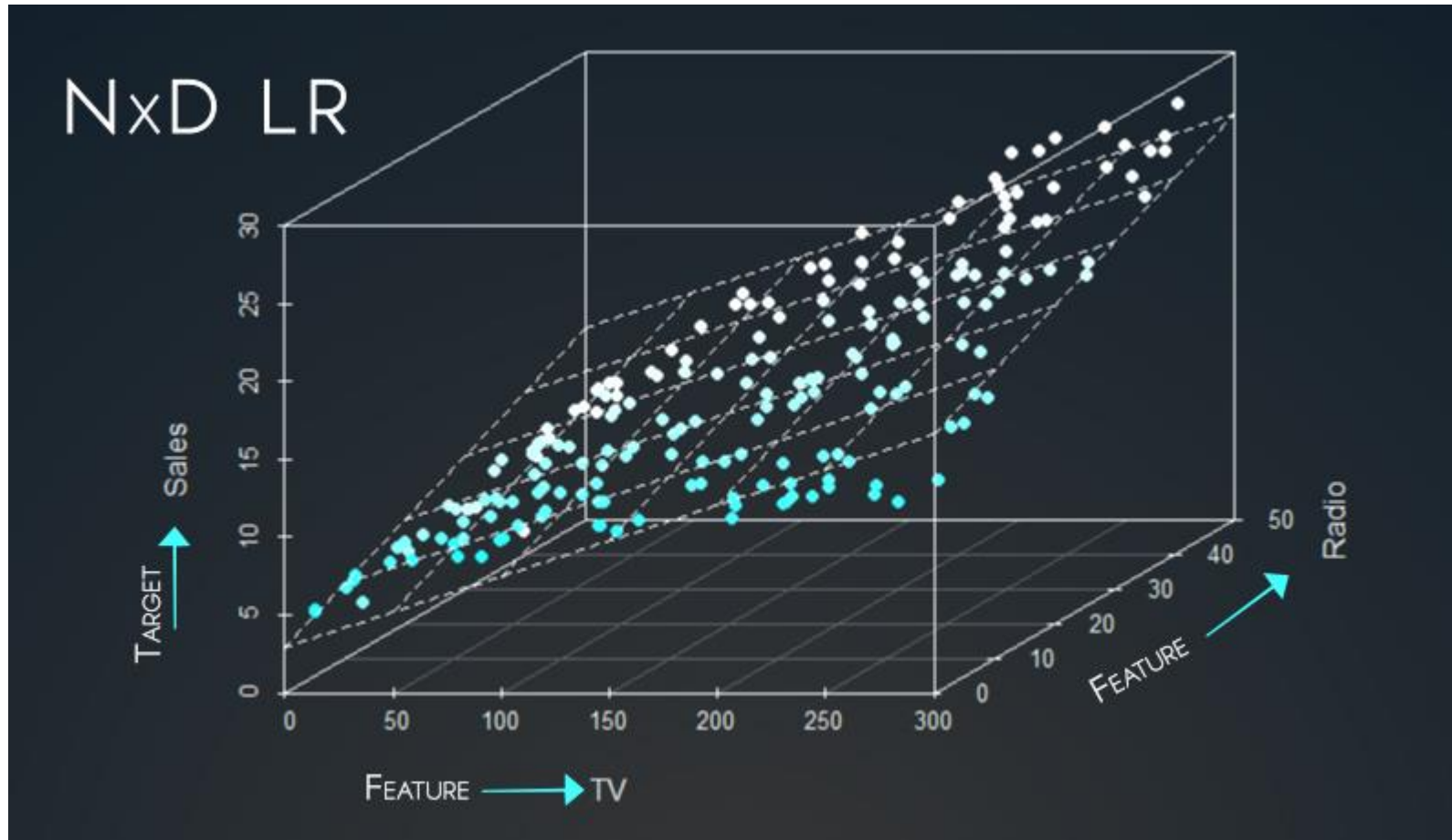
## C02 Sensor

Error with different temperatures, humidity and pressure

$$C02 = \text{Sensor} \cdot x0 + \text{temp} \cdot x1 + \text{hum} \cdot x2 + \text{pres} \cdot x3$$

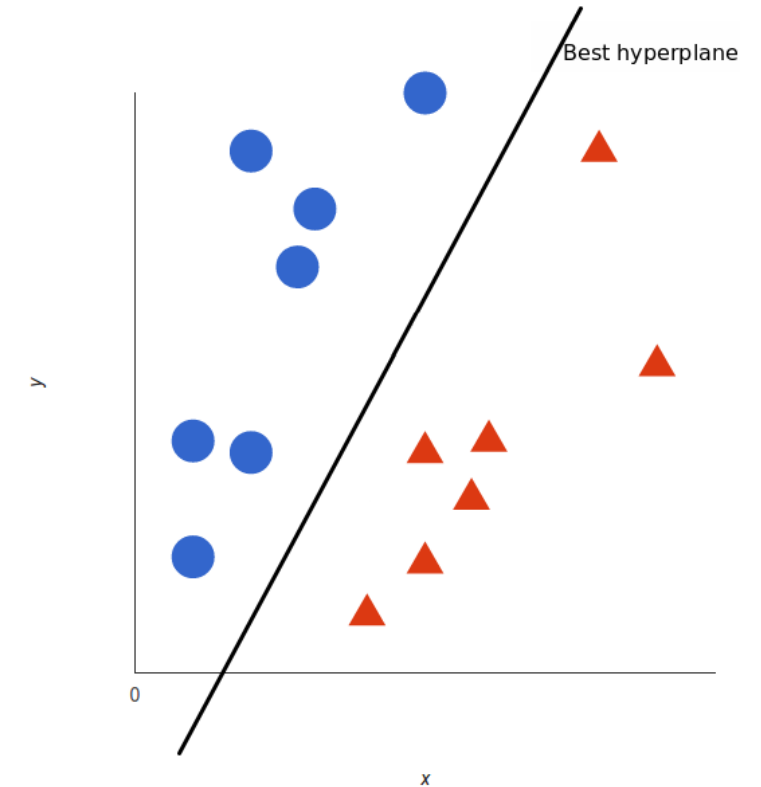
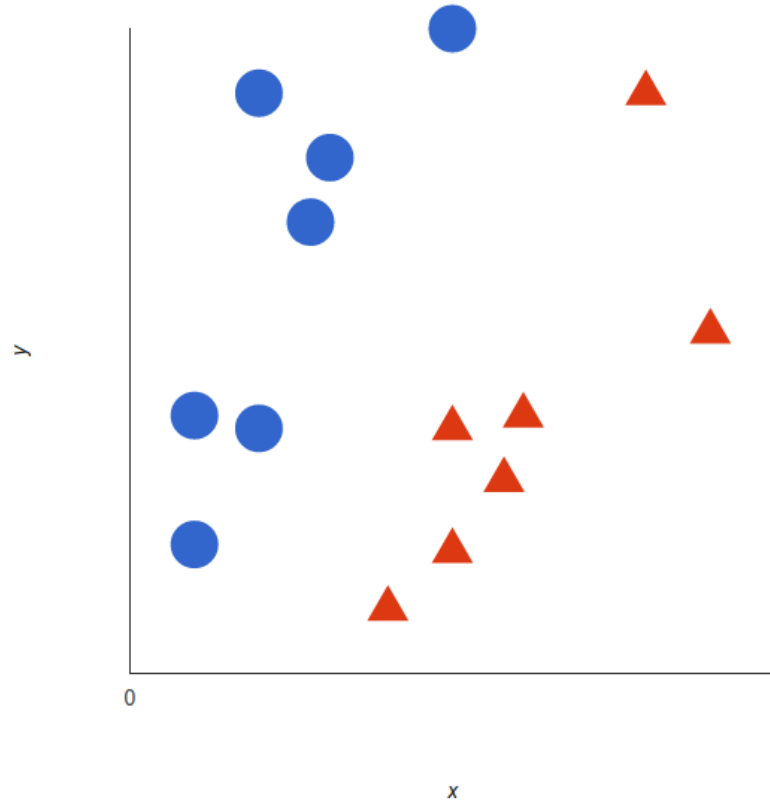


What for features do we have?

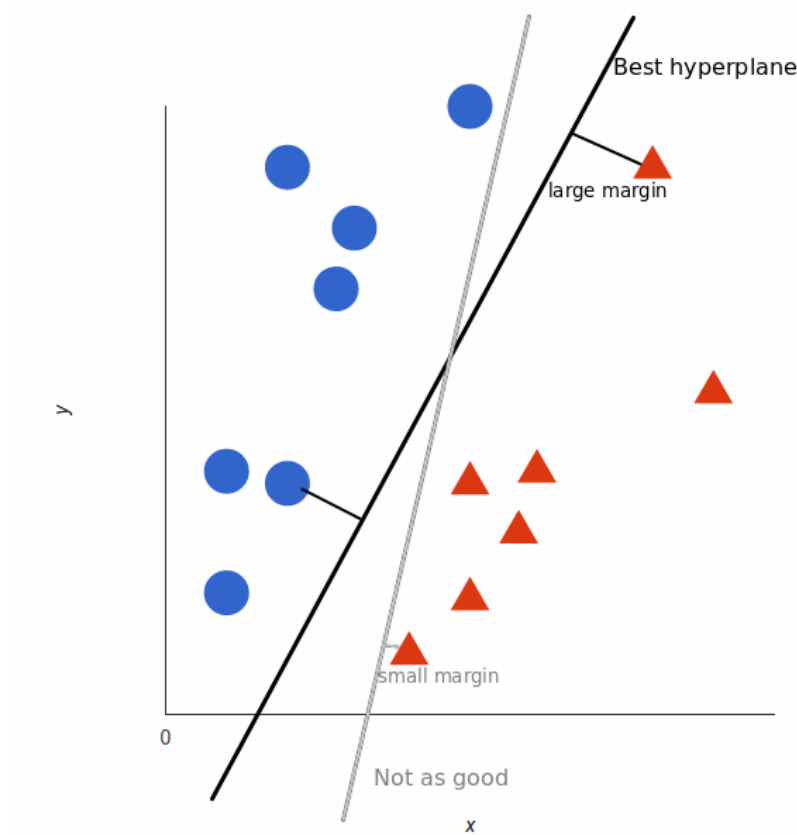




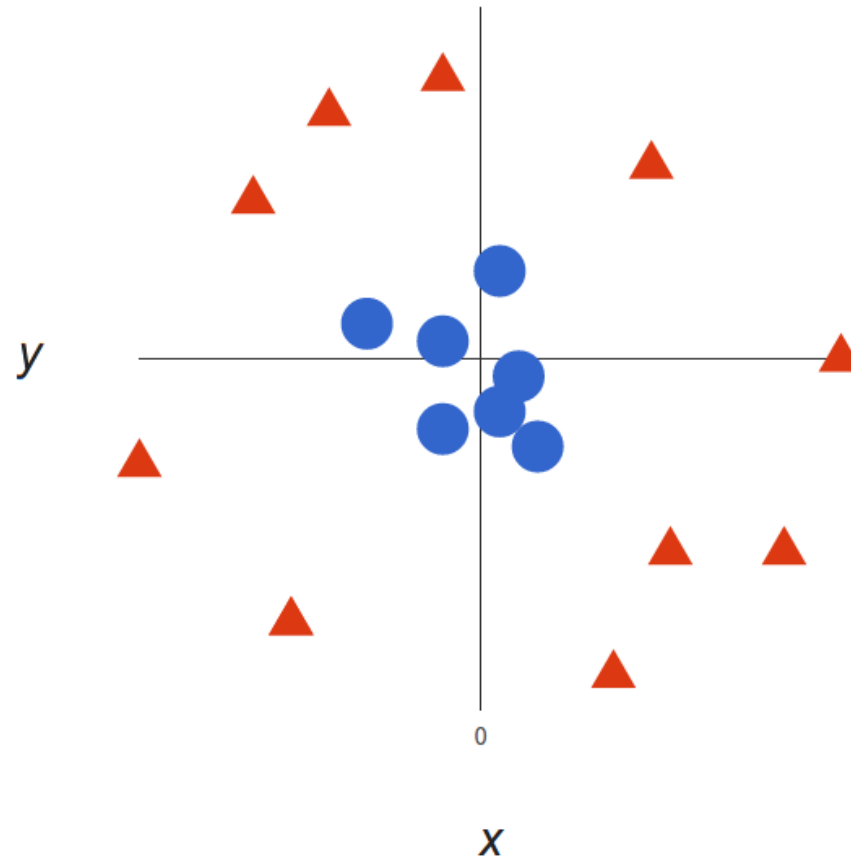
# Support Vector Machines



# But, what exactly is the best hyperplane?



# Nonlinear data



# Questions

What is linear regression?

What is it used for?

How do we get the linear model? Name 2 Methods. And when do you use them.

Explain the steps of the gradient decent.

What is SVM used for?

Which features do we have for example in a House Price calculator with linear regression?

What is the kernel trick?

Calculate a linear regression model for this Datapoints

N	X	Y
0	1	2
1	2	3
2	3	7
3	4	8

