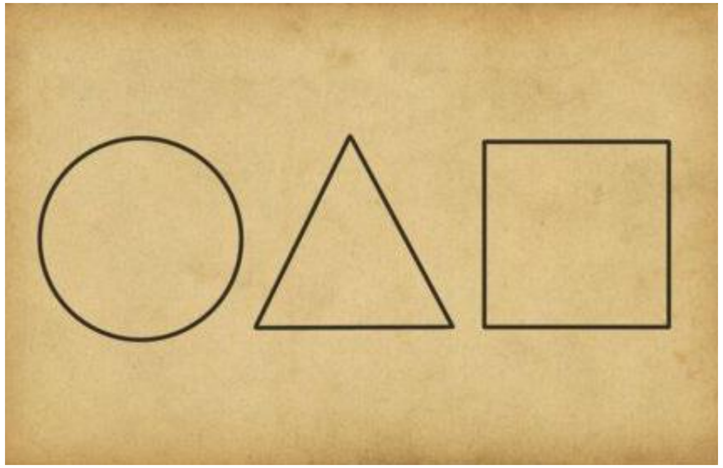
General

- Everything is on dl4cv.github.io (and Moodle)
- In-person (except me)
- 4 credit points (except chemistry ☹)
- 2 hrs. lecture, 1 hr. tutorial (Tutorial covers new material)
- All communication through Moodle, or dl4cv.wis@gmail.com
- 4 homework assignments + Final Project

Homework is demanding, but worth it

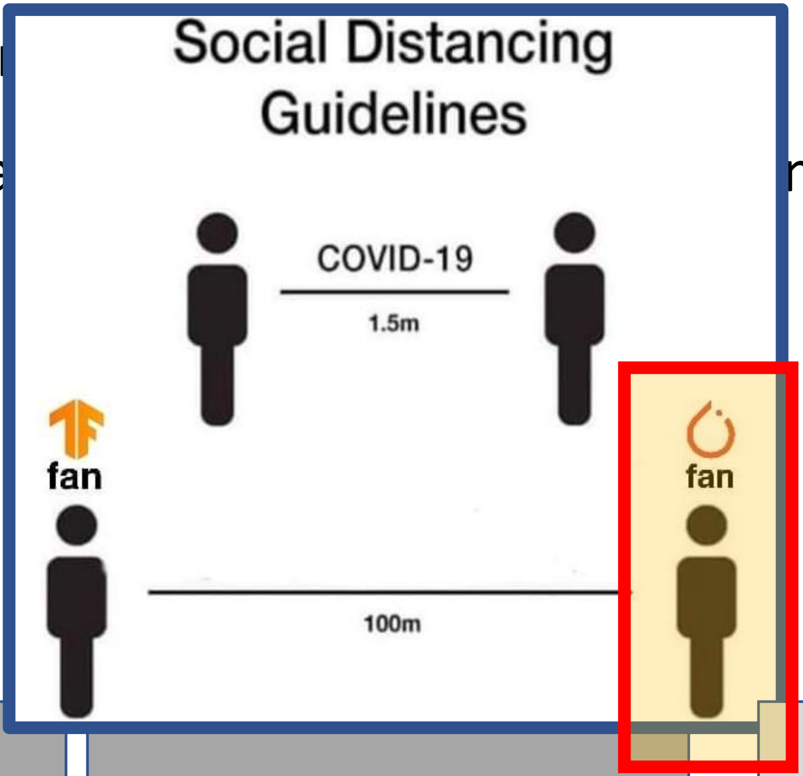


”If we have seen further, it is by standing on the shoulders of Giants"

- From basic to most recent SotA
- Slightly biased towards Weizmann research
- Intuition
- Hands-on
- Openness

We Assume you…

- Know Basic Calculus (e.g. know what is a Gr
- Know Basic Algebra (e.g. Vector spaces, Ma mposition).
- Written code before (preferably Python).
- Bumped into Machine Learning (e.g. heard



Homework

Theory	**From Scratch**	**Applied**	**HW1 is online!**

Road map

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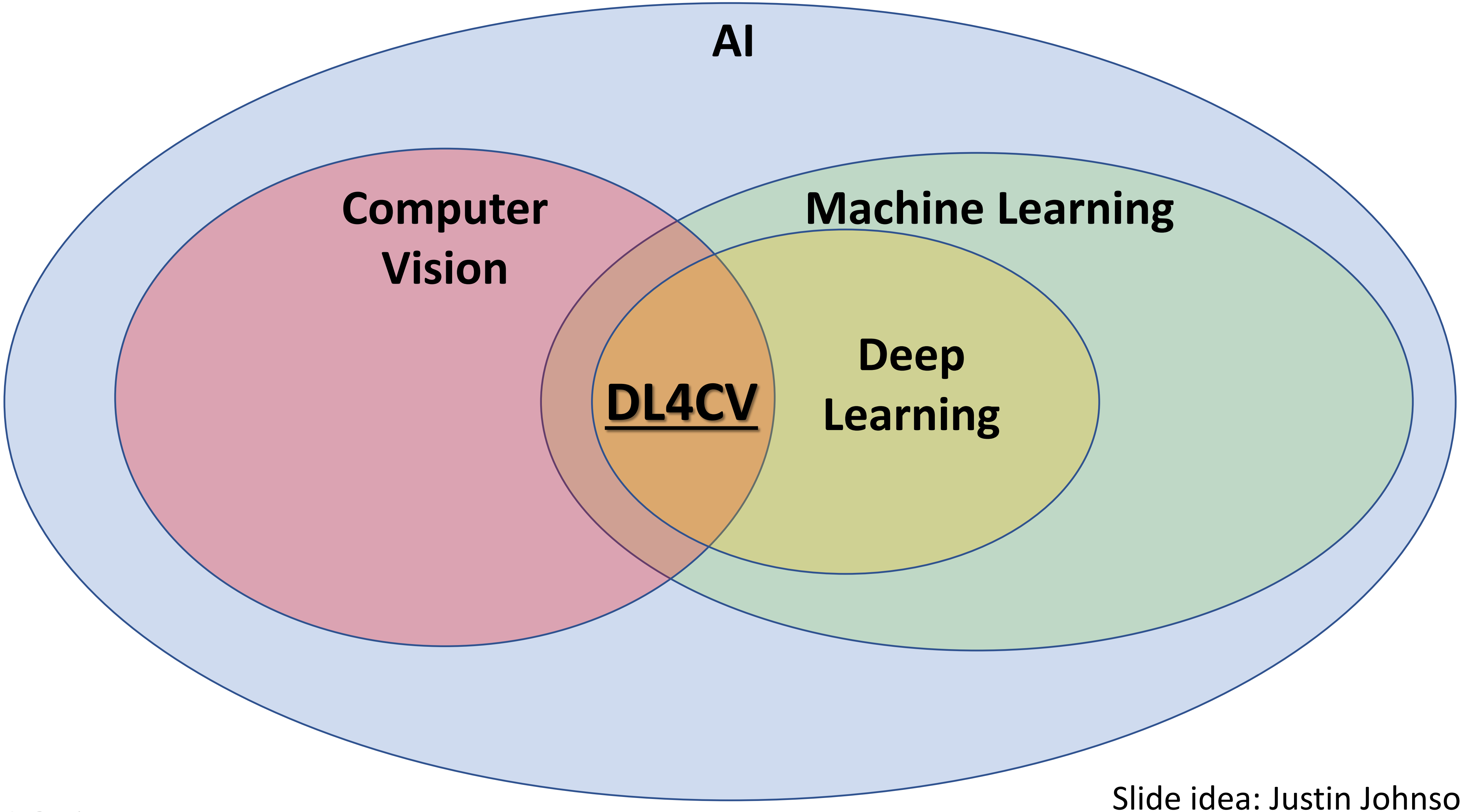
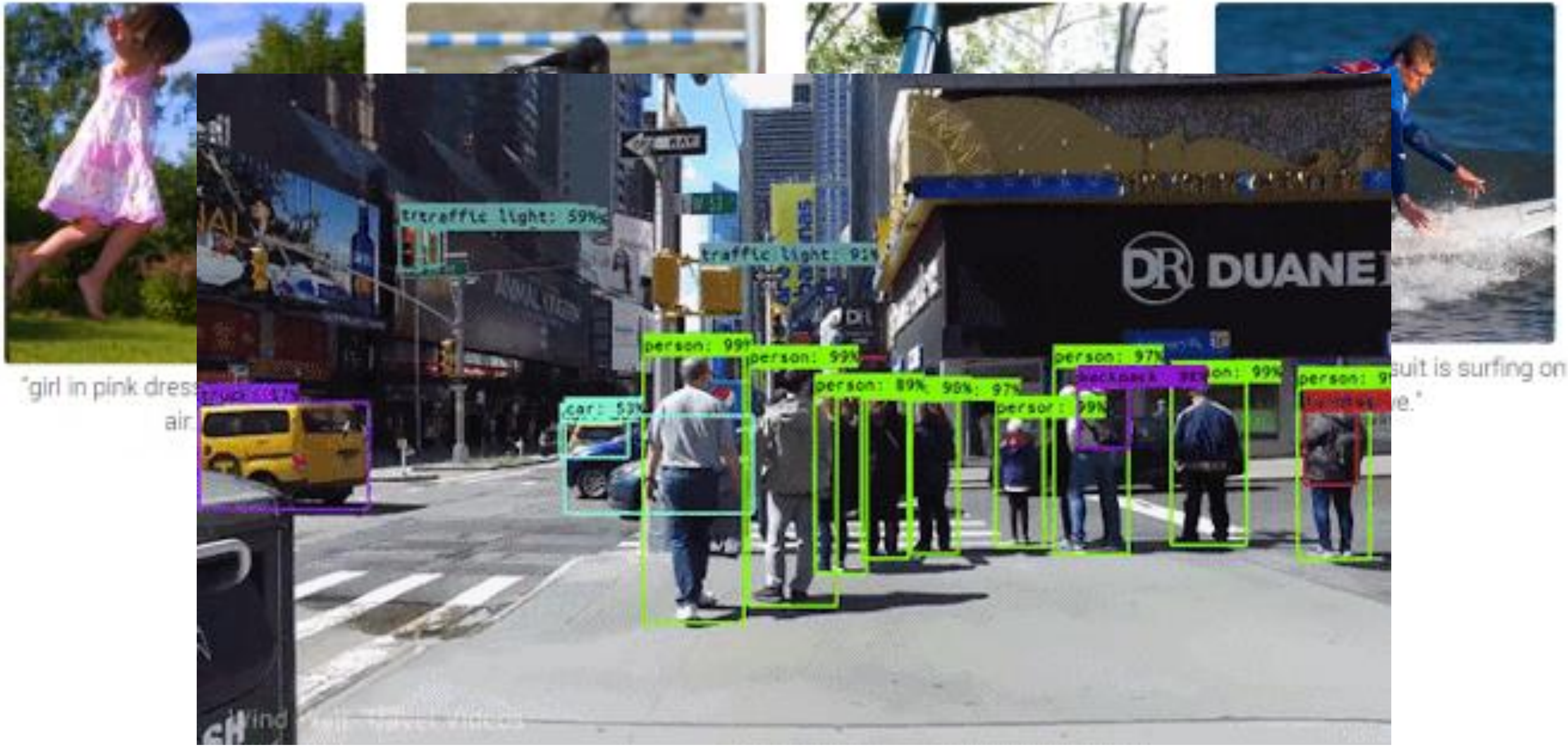


Slide idea: Justin Johnson

Today:

- Motivation and history (15%)
- Supervised learning (25%)
- Linear regression (20%)
- Gradient descent (25%)
- Feature transform (15%)

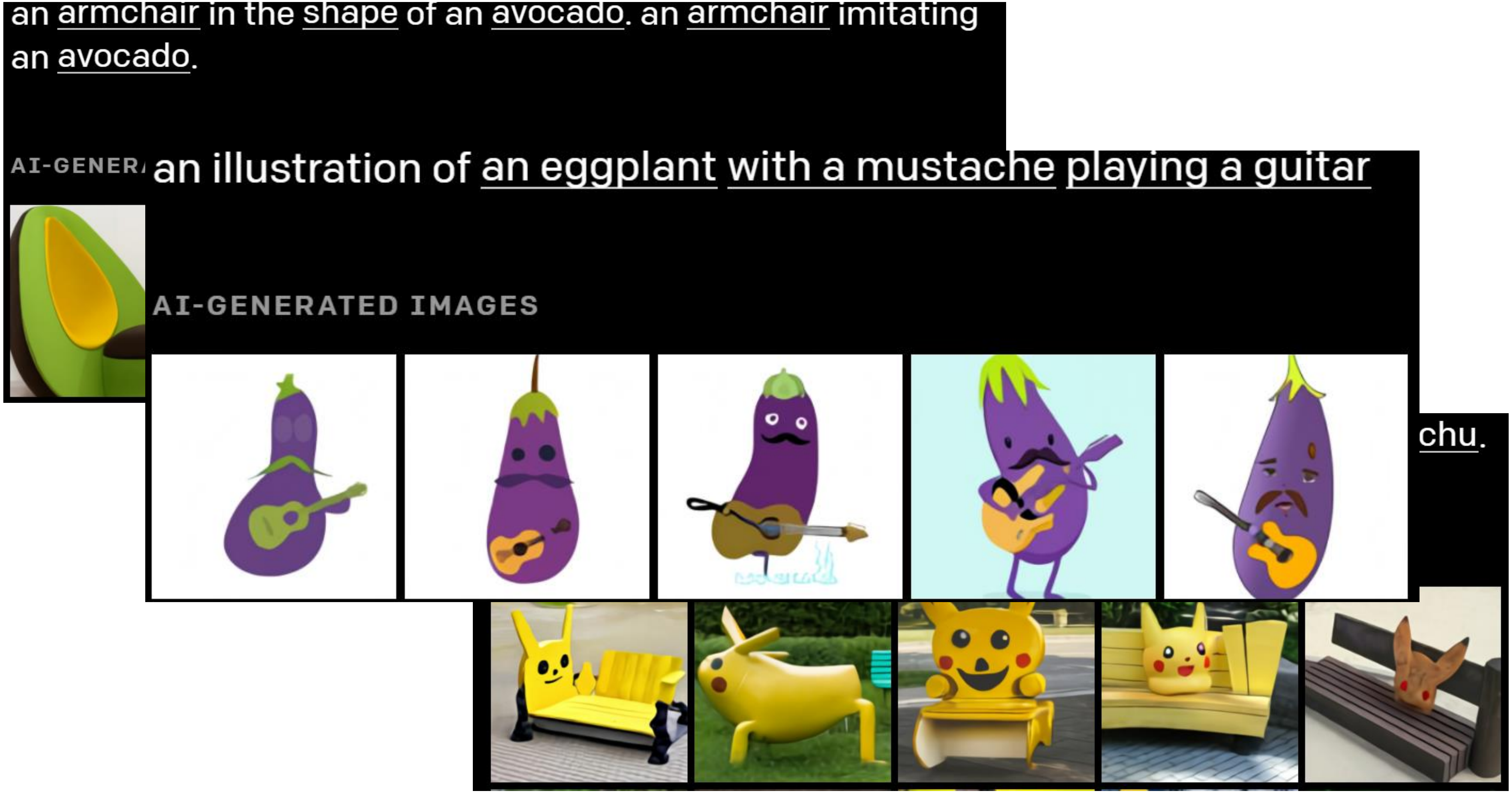
Deep Learning is powerful



Andrej Karpathy, Li Fei-Fei, CVPR 2015 Deep Visual-Semantic Alignments for Generating Image Descriptions

Abhishek Bansal- DetectMe (GitHub)

Deep Learning is powerful!

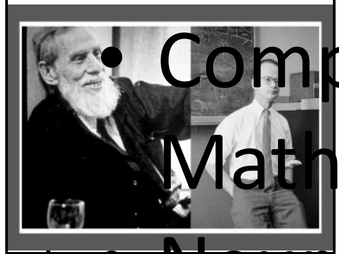


Ramesh et al. Zero-Shot Text-to-Image Generation (Dall-E); 2021

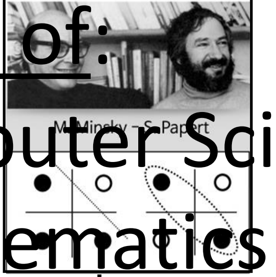
History of:

- Computer Science
- Mathematics
- Neuroscience

McCulloch Pitts
Non learned
Neuron



XOR kills perceptron



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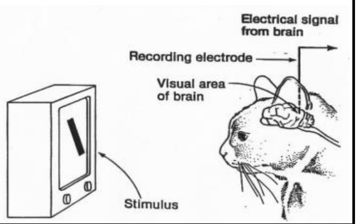
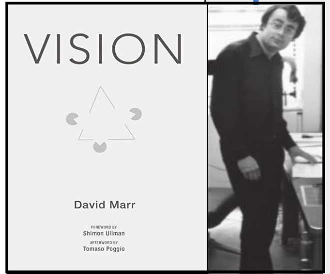
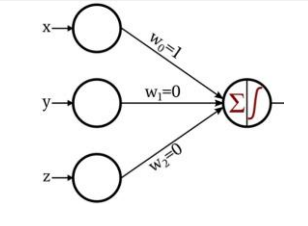
Hubel & Wiesel



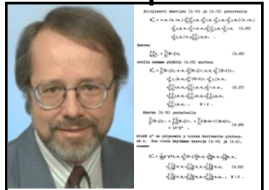


1957 1970

1943 1959 1969 1979

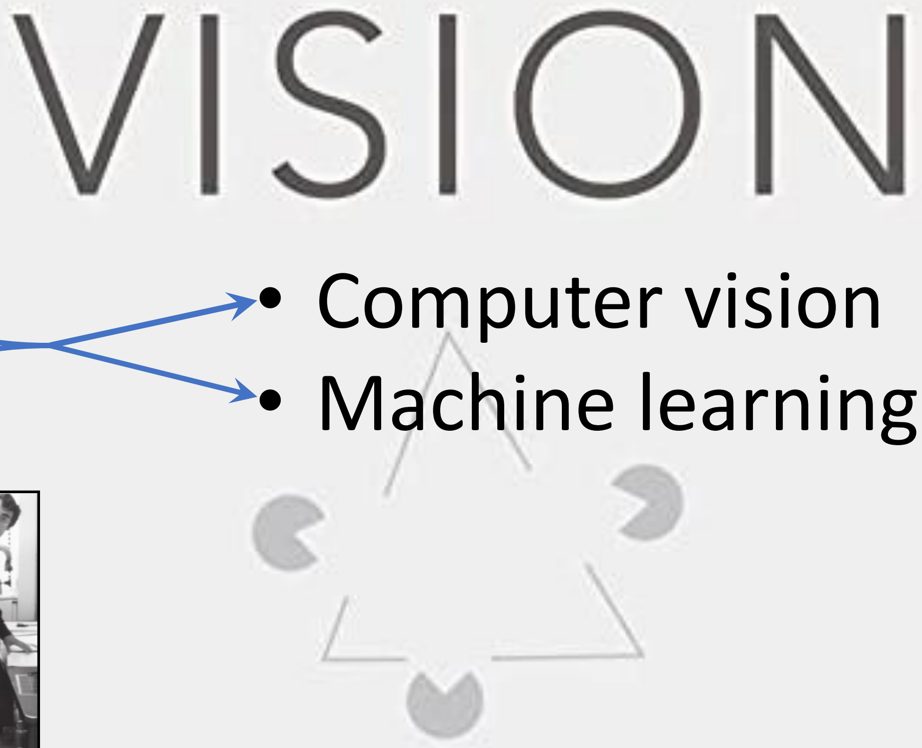


Perceptron (Rosenblatt) learned weights



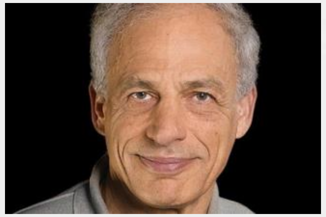
Back Propagation (Linnainmaa)

1st AI Winte



- Computer vision
- Machine learning

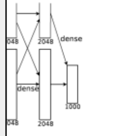
David Marr



FOREWORD BY
Shimon Ullman

AFTERWORD BY
Tomaso Poggio

egins!
Hinton



ANs
Good
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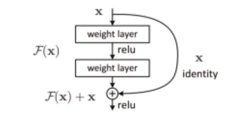
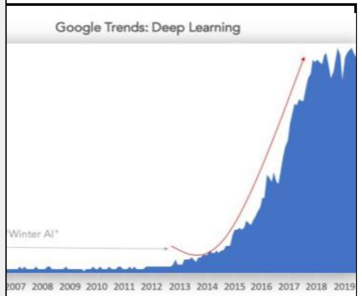
Bengio, Hinton, LeCunn
Turing Award



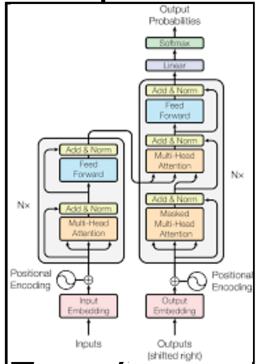
ResNet (He)

2017

2014 2015 2018



Deep Learning revolution



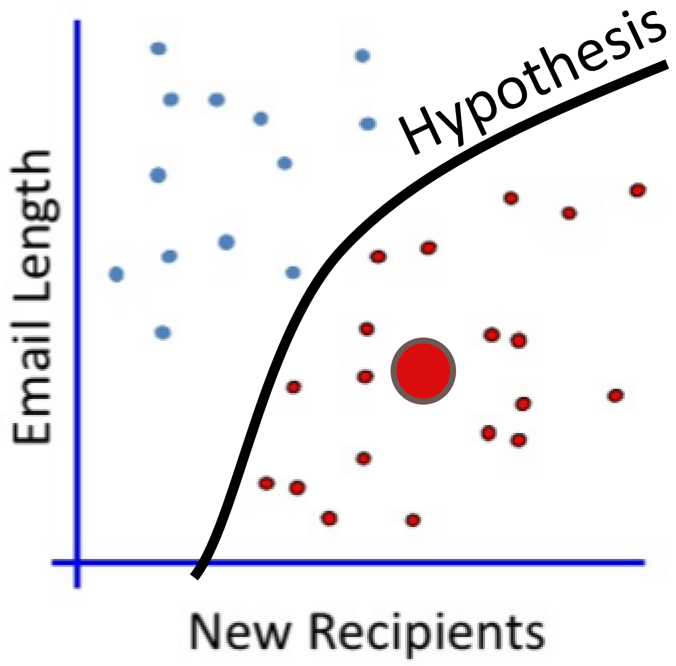
Transformer (Vaswani)

Supervised Learning

Features | Labels

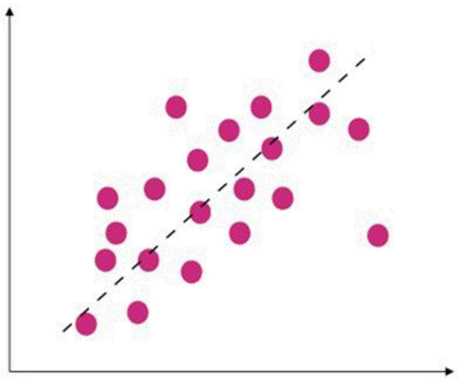
	Number of new Recipients	Email Length (K)	Country (IP)	Customer Type	Email Type
Instances	0	2	Germany	Gold	Ham
	1	4	Germany	Silver	Ham
	5	2	Nigeria	Bronze	Spam
	2	4	Russia	Bronze	Spam
	3	4	Germany	Bronze	Ham
	0	1	USA	Silver	Ham
	4	2	USA	Silver	Spam

Numeric | Nominal | Ordinal

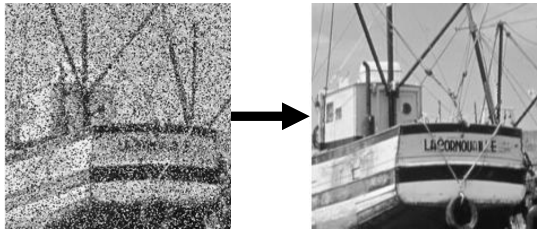


Supervised Learning

Regression

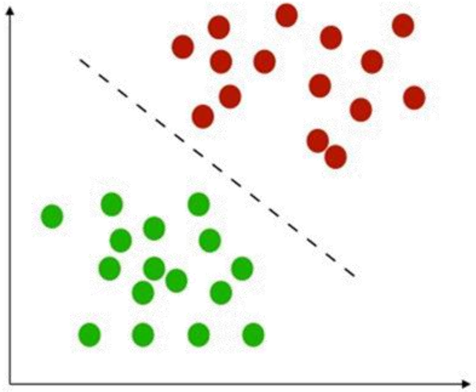


E.g. Image denoising



E.g. Object localization

Classification



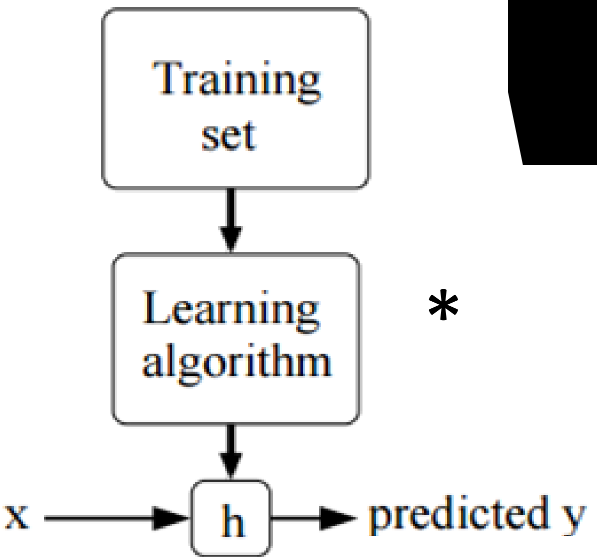
E.g. Image classification

Supervised Learning

Learning Algorithm | Training set | Hypothesis

$$A(S) = h$$

- *Hypothesis class* $\mathcal{H} = \{h_1, h_2 \dots\}$
  - $h(x) \approx y$
- *Loss* $\mathcal{L}$
- *Optimization method*



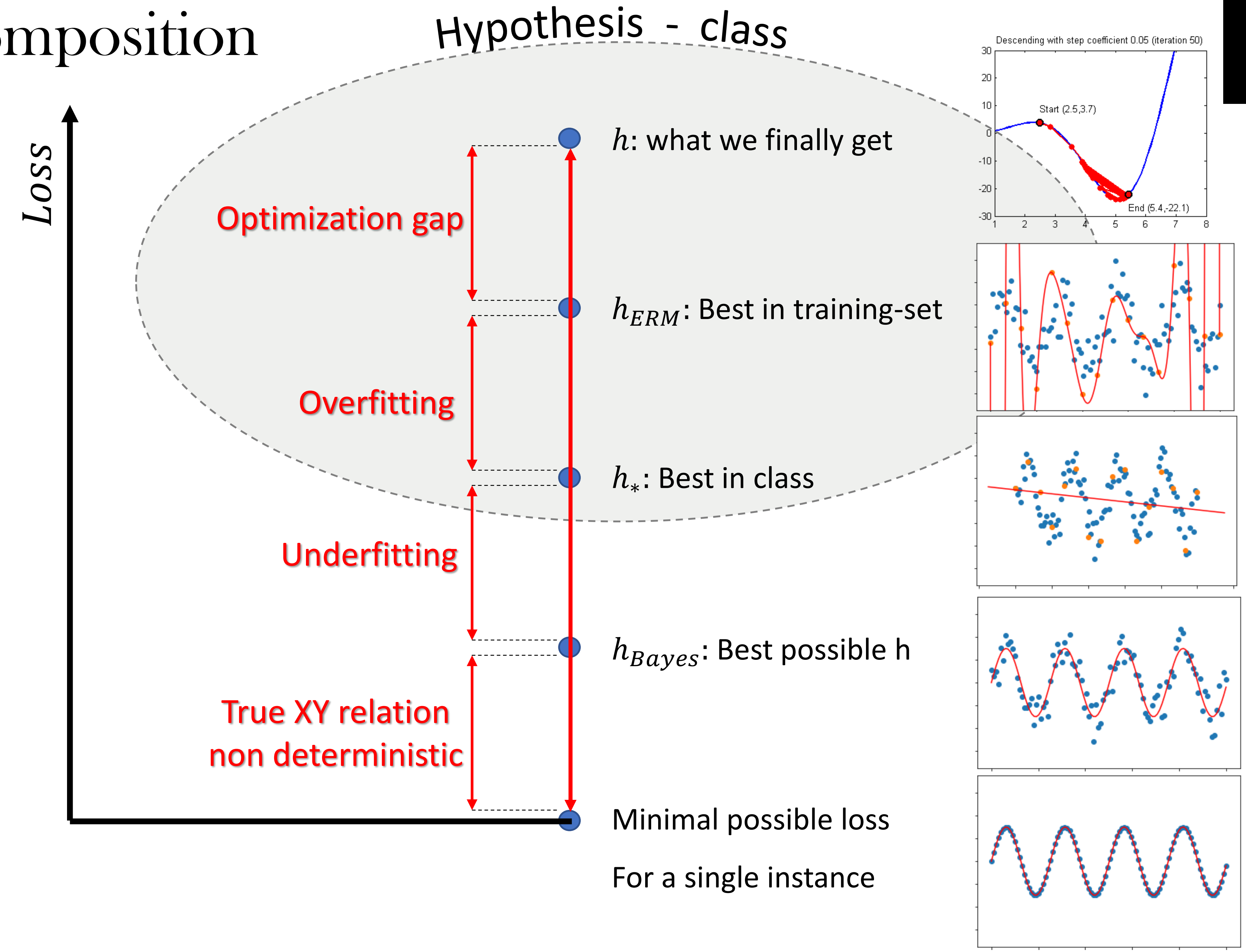
*

Inputs ***X***, *Labels* ***Y***

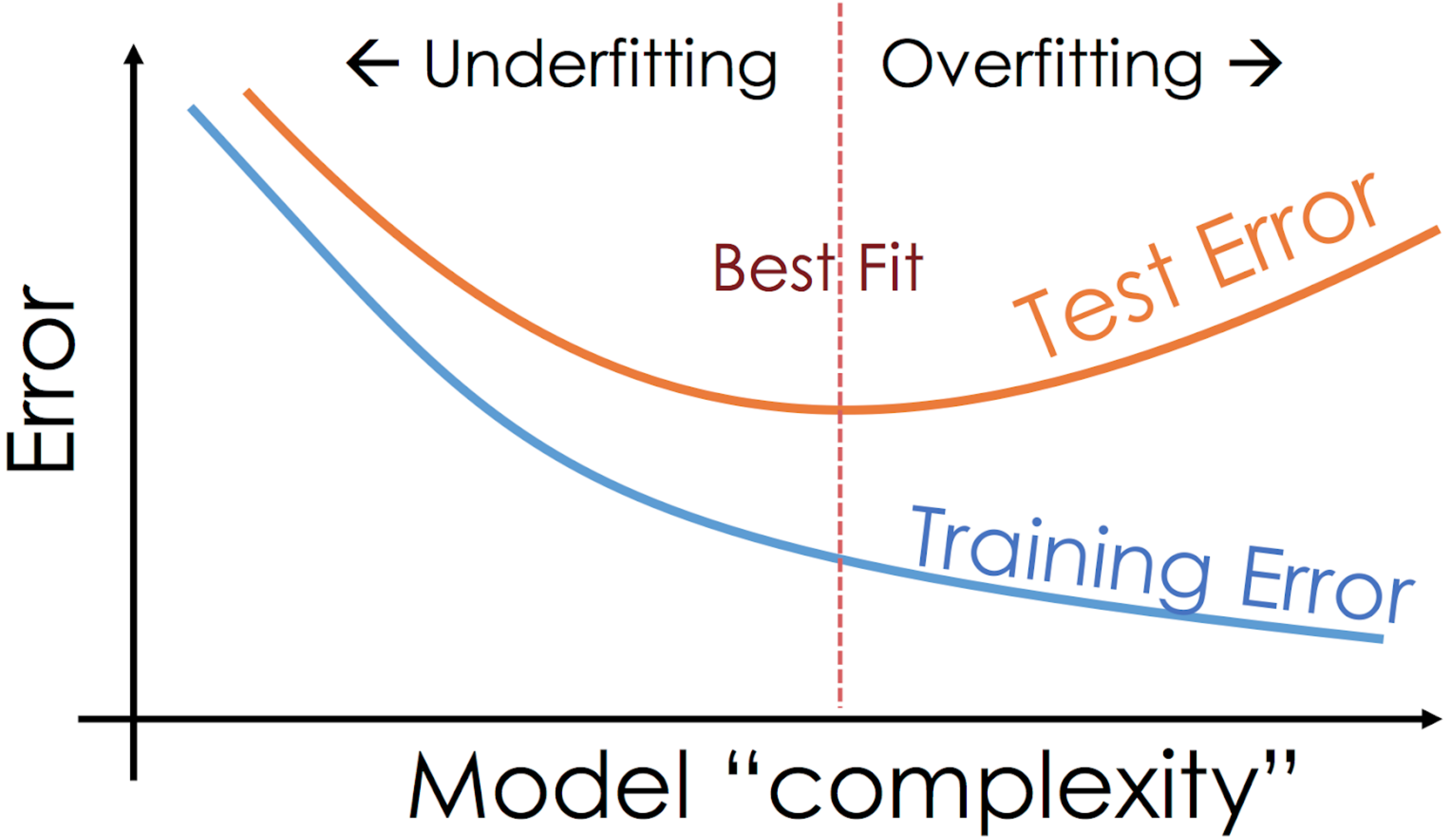
$$\begin{bmatrix} \text{———} & \mathbf{x_1}^T & \text{———} \\ \text{———} & \mathbf{x_2}^T & \text{———} \\ & \vdots & \\ \text{———} & \mathbf{x_M}^T & \text{———} \end{bmatrix}, \begin{bmatrix} \text{—} & \mathbf{y_1}^T & \text{—} \\ \text{—} & \mathbf{y_2}^T & \text{—} \\ & \vdots & \\ \text{—} & \mathbf{y_M}^T & \text{—} \end{bmatrix}$$

* Diagram by Andrew NG

Error decomposition



Generalization



Overfitting- Data influence

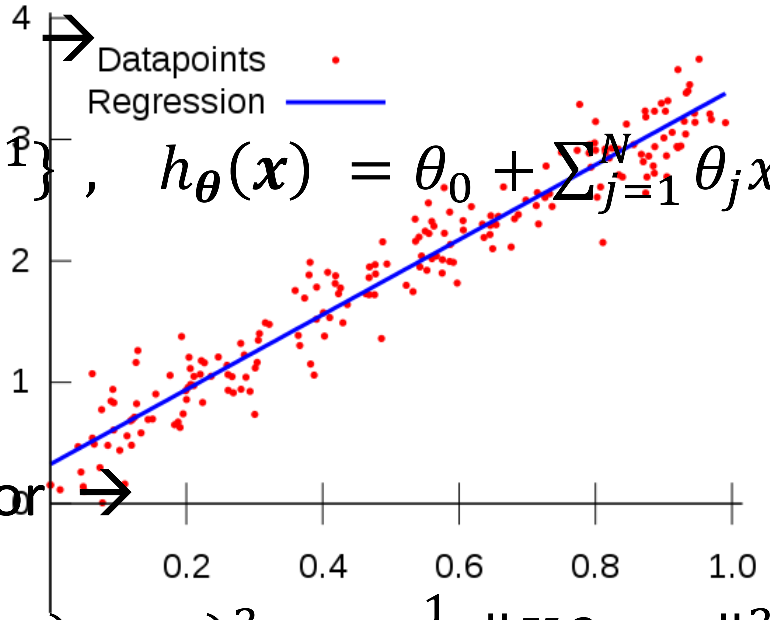
[redacted]

Matrix A

$$\begin{bmatrix} 3 & 4 \\ 6 & 8 \end{bmatrix}$$

Linear Regression

Hypothesis class: Linear →



$$\mathcal{H} = \{h_{\boldsymbol{\theta}} \mid \boldsymbol{\theta} \epsilon\ \mathbb{R}^{N+1}\}\ , \quad h_{\boldsymbol{\theta}}(\boldsymbol{x}) = \theta_0 + \sum_{j=1}^{N} \theta_j x_j = \theta_0 + \tilde{\boldsymbol{\theta}}^T \boldsymbol{x} = \boldsymbol{\theta}^T \begin{pmatrix} 1 \\ | \\ \boldsymbol{x} \\ | \end{pmatrix}$$

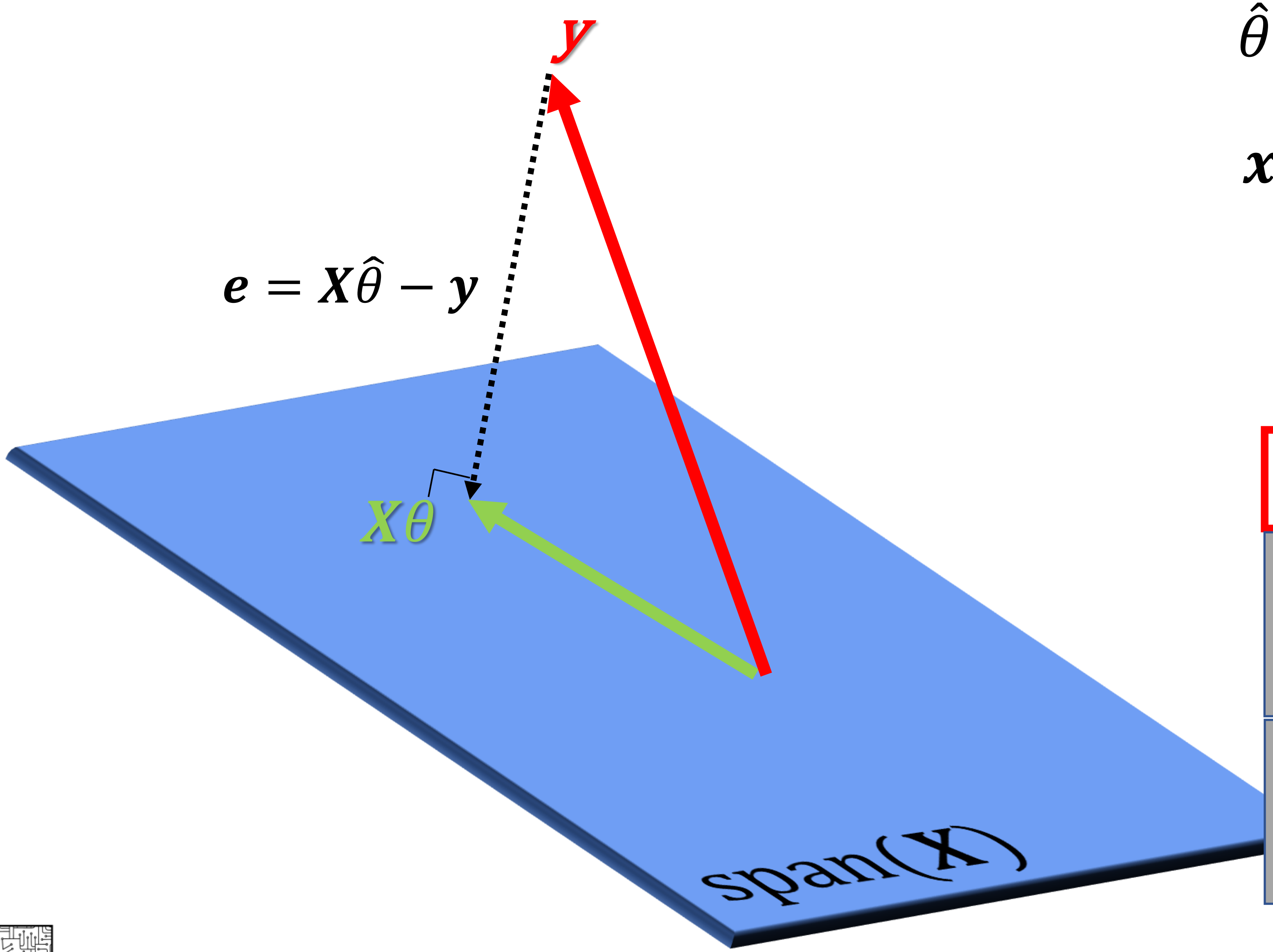
*Bias= Just add **1** at top of the input vec!*

Loss: Mean Squared Error →

$$\mathcal{L} = \frac{1}{2M} \sum_{i=1}^{M} \left(h_\theta(\boldsymbol{x}_i) - y_i\right)^2 = \frac{1}{2M} \|\boldsymbol{X\theta} - \boldsymbol{y}\|^2$$

Optimization method: Normal equations / Gradient Descent

Normal Equations (intuition)



$$\hat{\theta} = argmin_{\theta} \|y - \boldsymbol{X}\theta\|^2$$

$$\boldsymbol{x} \perp \boldsymbol{e} \quad \forall\ x \in span(\boldsymbol{X})$$

$$\Downarrow$$

$$\boldsymbol{X}^T(\boldsymbol{X}\hat{\theta} - \boldsymbol{y}) = 0$$

$$\Downarrow$$

$$\hat{\theta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y} \quad *$$

Formal proof: HW

Also in HW:
is $X^T X$ invertible?

$* \ if\ \boldsymbol{X}^T\boldsymbol{X}\ invertible$

Normal Equations

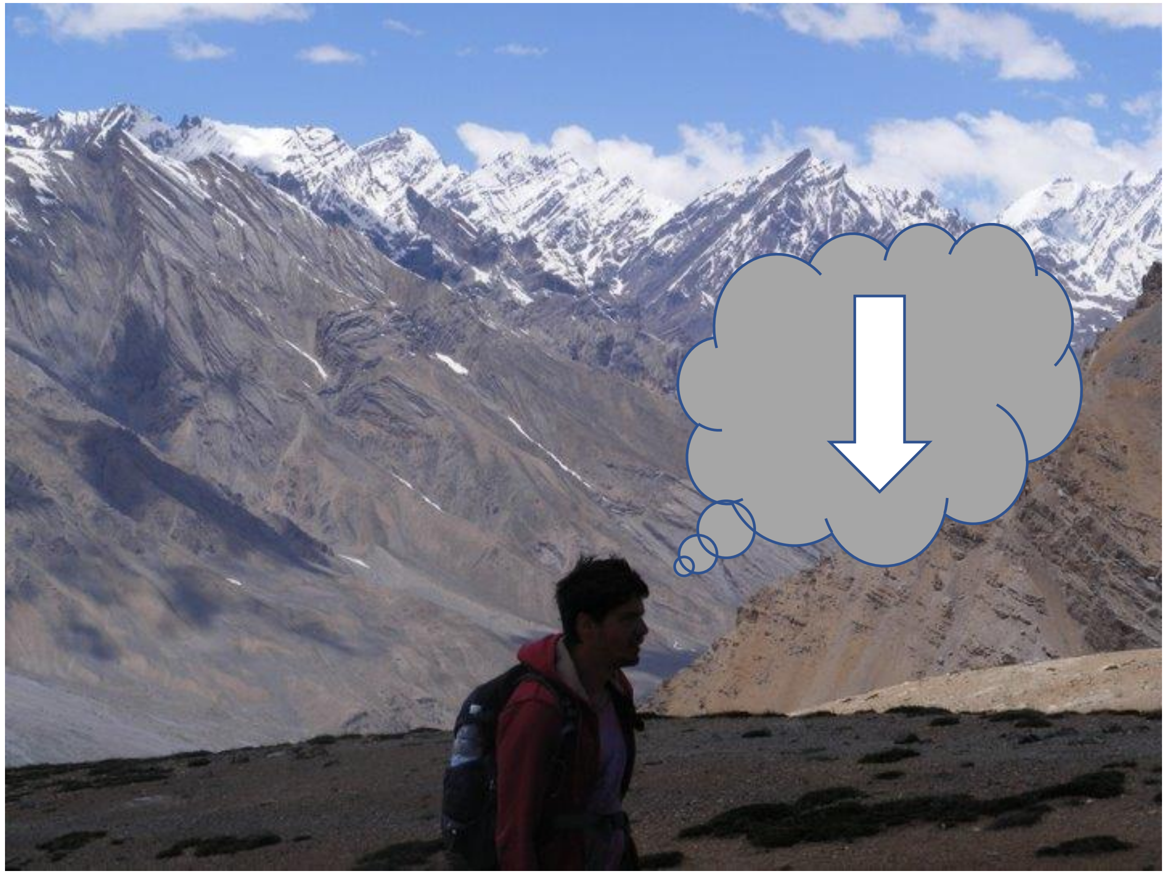
Q: Will normal equations always be practical?

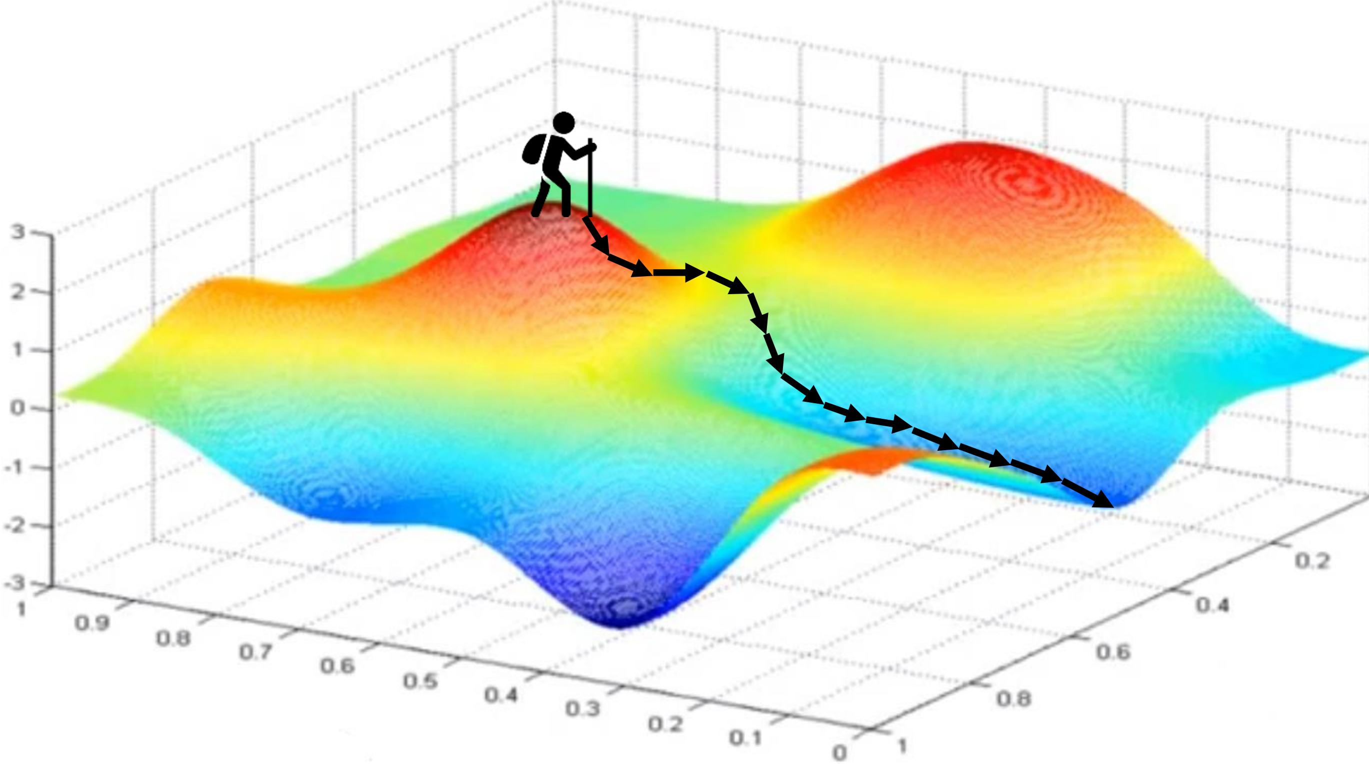
A: No;

1. Inverting $\boldsymbol{X}^T\boldsymbol{X}$ may cost unreasonable memory / time
2. Sometimes not applicable: Regularization? Different loss? More layers?

Gradient descent

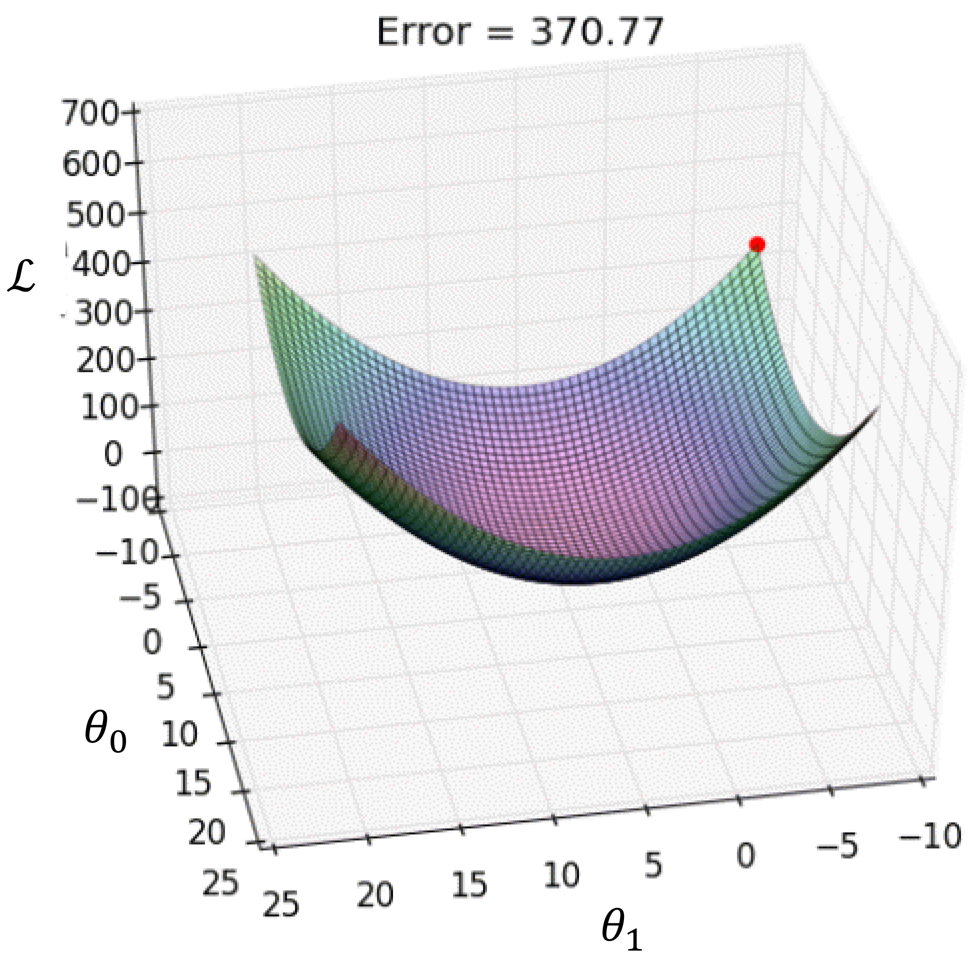
Possible solution: Iteratively reduce loss

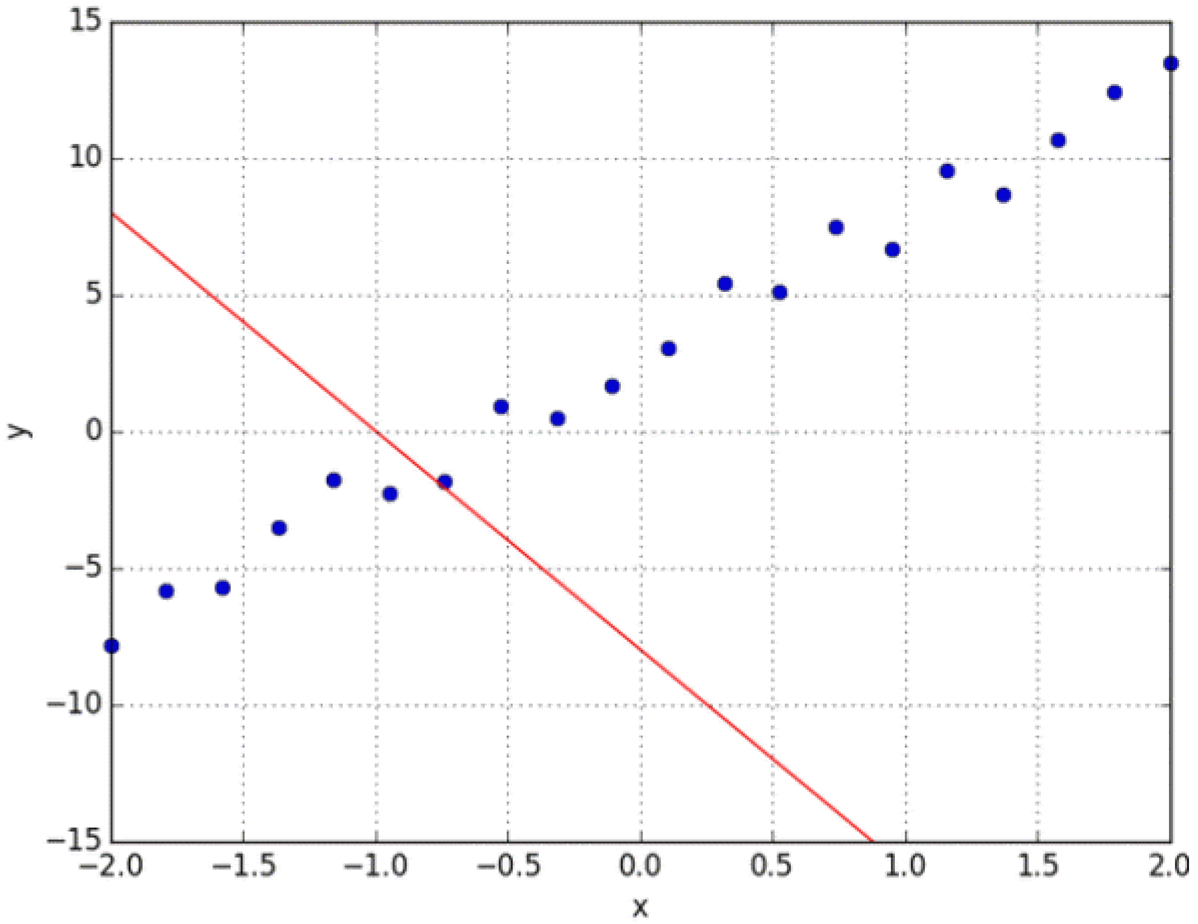




Can we guarantee global min?

Gradient descent





Parameter space: $\mathcal{L}(\boldsymbol{\theta}; S)$

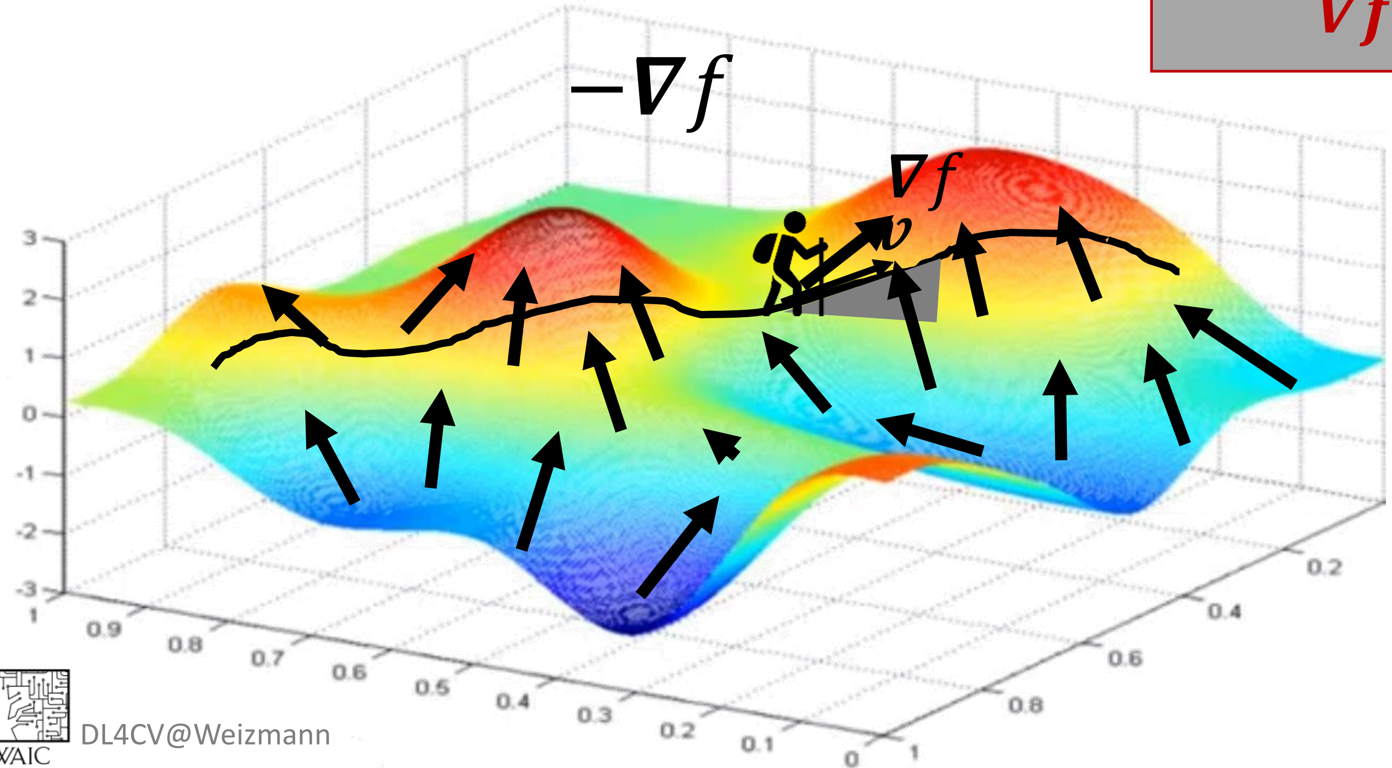
Data space: $h_{\boldsymbol{\theta}}(\boldsymbol{x})$

Calculus reminder: Directional derivative

$$\lim_{\varepsilon\to 0}\frac{f(\boldsymbol{x}+\varepsilon\boldsymbol{v})-f(\boldsymbol{x})}{\varepsilon\|\boldsymbol{v}\|} = \frac{1}{\|\boldsymbol{v}\|}\sum v_i\frac{\partial f}{\partial x_i} = \frac{\boldsymbol{v}^T}{\|\boldsymbol{v}\|}\begin{pmatrix}\frac{\partial f}{\partial x_1}\\ \frac{\partial f}{\partial x_2}\\ \vdots\\ \frac{\partial f}{\partial x_N}\end{pmatrix} = \frac{1}{\|\boldsymbol{v}\|}\langle \boldsymbol{v}, \boldsymbol{\nabla} f\rangle$$

If differentiable

Gradient!
$\vec{\boldsymbol{\nabla}} \boldsymbol{f}$



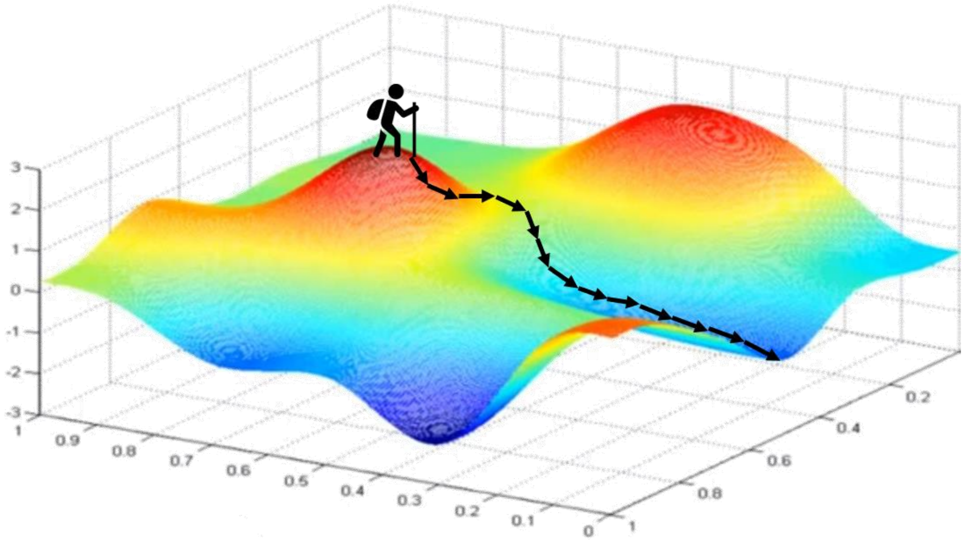
<u>According to Cauchy-Schwarz inequality</u>:

- Max value is $\|\boldsymbol{\nabla} f\|$
- Obtained when $\boldsymbol{v}$ is parallel to $\boldsymbol{\nabla} f$

- Gradient directs to steepest ascent.
- It's size is the max steepness.

Gradient descent

$$\boldsymbol{\nabla}\mathcal{L}(\theta_0, \theta_1 \dots \theta_N) = \begin{pmatrix} \frac{\partial \mathcal{L}}{\partial \theta_0} \\ \frac{\partial \mathcal{L}}{\partial \theta_1} \\ \vdots \\ \frac{\partial \mathcal{L}}{\partial \theta_N} \end{pmatrix}$$



Augustin Louis Cauchy

1. Initialize $\theta \sim \text{Random}$
2. Repeat until convergence:

   {

   $$\boldsymbol{\theta} \coloneqq \boldsymbol{\theta} - \alpha \boldsymbol{\nabla}\mathcal{L}(\boldsymbol{\theta}; S)$$

   }

α: Learning rate

Gradient descent

Full batch Gradient Descent

$$\boldsymbol{\theta} := \boldsymbol{\theta} - \alpha \boldsymbol{\nabla} \mathcal{L}(\boldsymbol{\theta}; S)$$

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gradient descent

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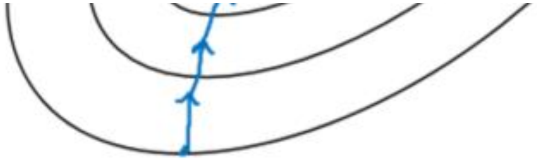


Figure by Z² Little on Medium

Gradient descent for Linear Regression

$$\mathcal{L} = \frac{1}{2m}\sum_{i=1}^{m}(\boldsymbol{\theta}^T\boldsymbol{x}_i - y_i)^2$$

$$\frac{\partial}{\partial\boldsymbol{\theta}}\mathcal{L} = \frac{1}{m}\sum_{i=1}^{m}(\boldsymbol{\theta}^T\boldsymbol{x}_i - y_i)\boldsymbol{x}_i = \frac{1}{m}\sum_{i=1}^{m}\boldsymbol{x}_i(\boldsymbol{X\theta} - \boldsymbol{y})_{\boldsymbol{i}} = \boldsymbol{X}^T\overbrace{(\boldsymbol{X\theta} - \boldsymbol{y})}^{\boldsymbol{e}}$$

Repeat until convergence:

{

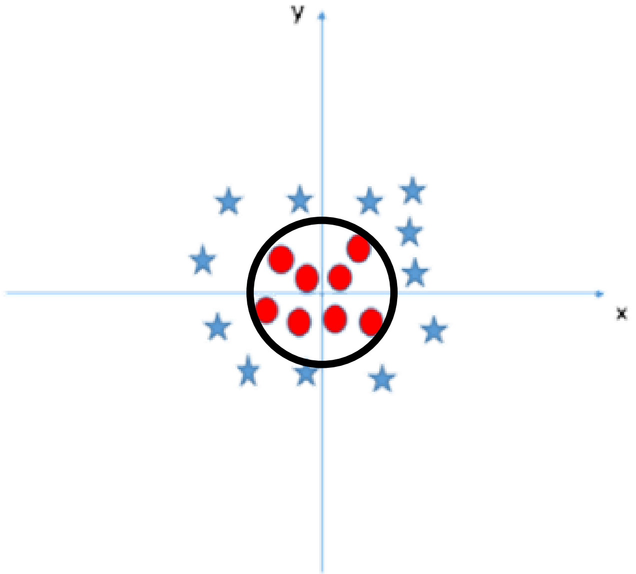
$$\boldsymbol{\theta} := \boldsymbol{\theta} - \frac{\alpha}{m}\boldsymbol{X}^T\boldsymbol{e}$$

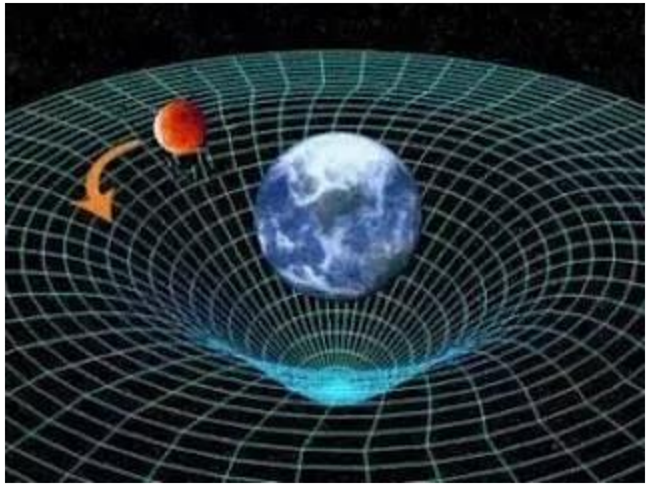
}

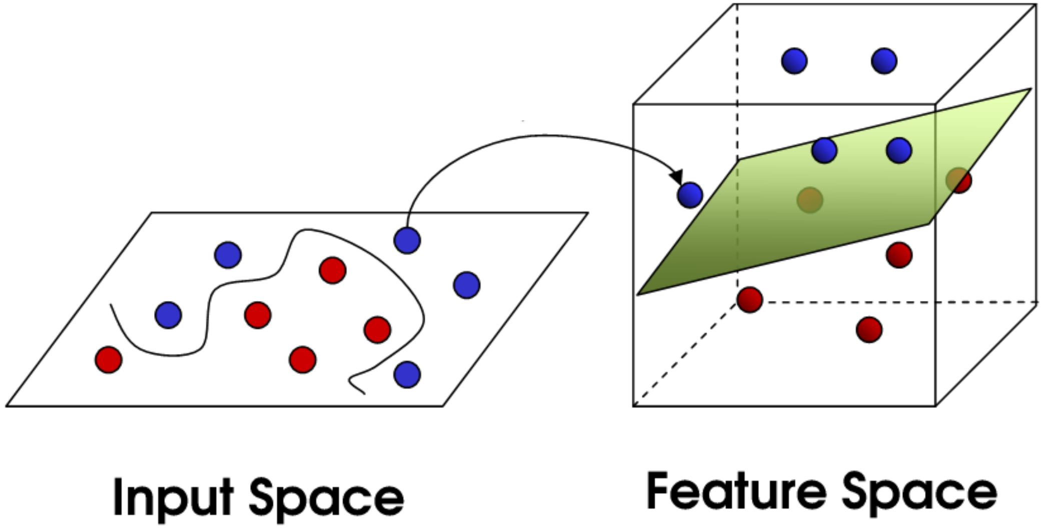
Q: Find the relation between convergence and Normal Equations

Feature transform

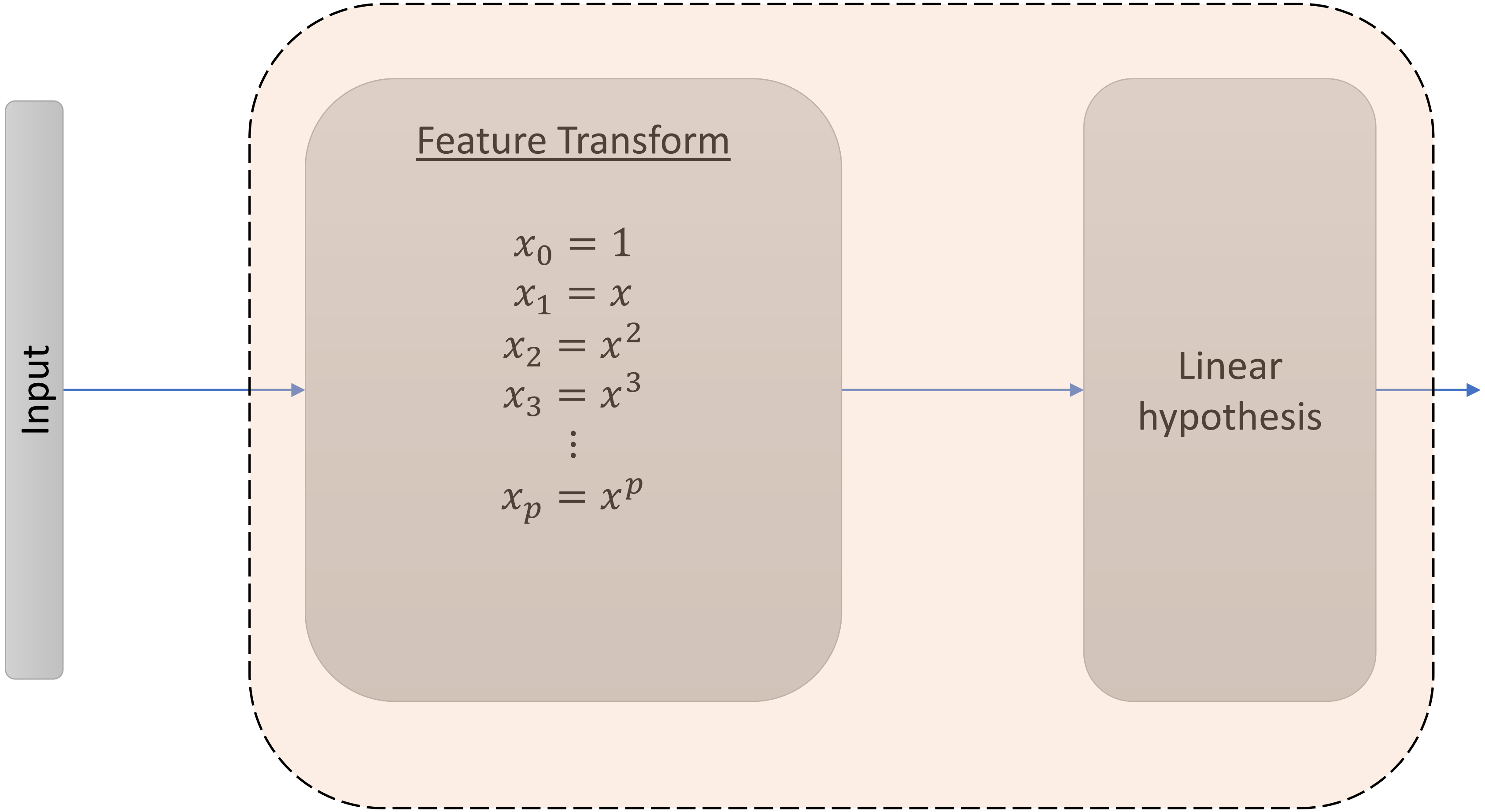
$$z = \sqrt{x^2 + y^2}$$





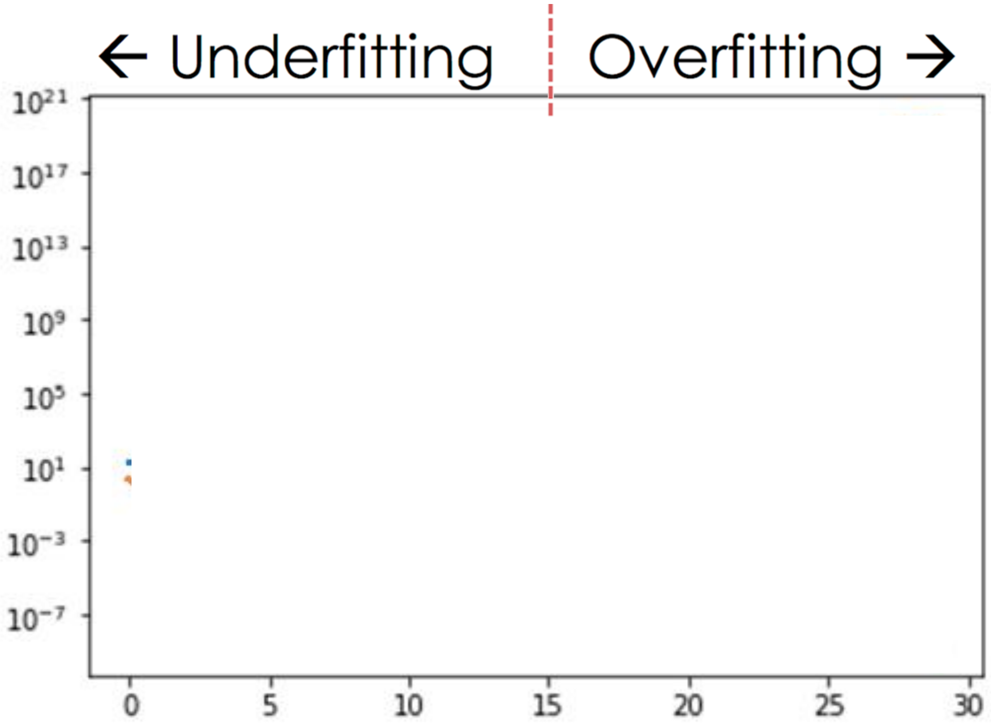


Feature transform



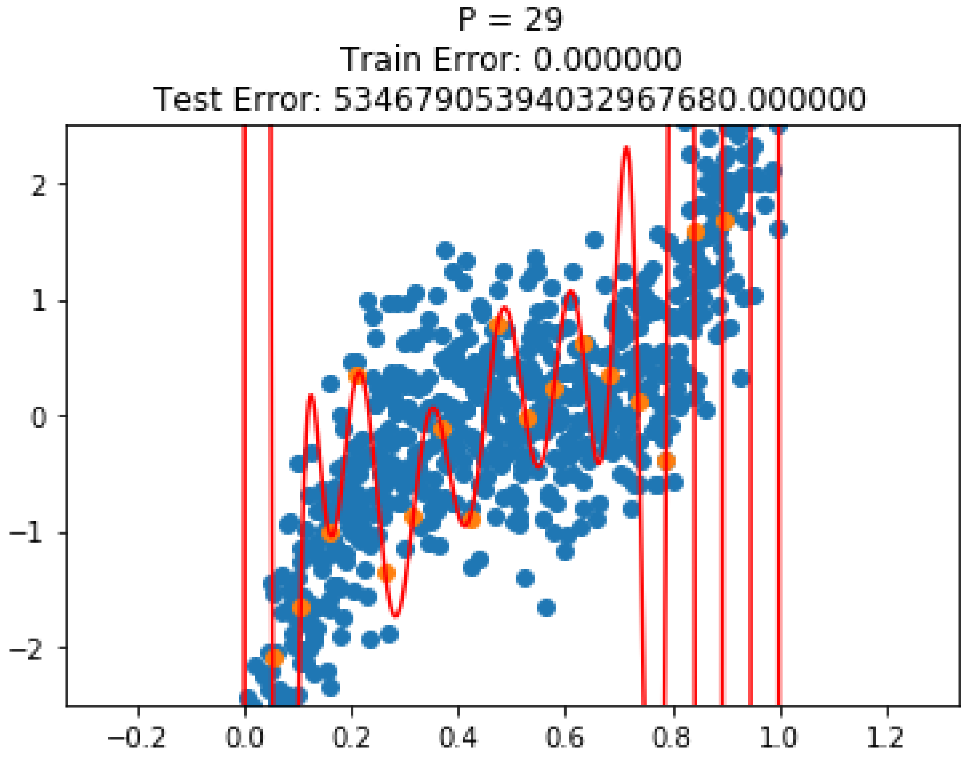
Non-linear hypothesis!
(Polynomial)

Polynomial fitting



Train

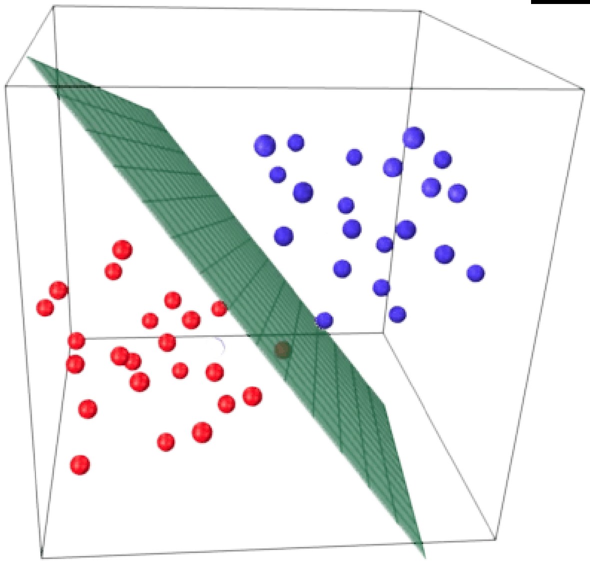
Test



This week's tutorial:

Or
Bar-Shira

Linear classification



Next week's lecture:

(Me Again)

Neural Networks