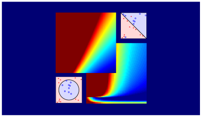
# Machine Learning Foundations
# (機器學習基石)



## Lecture 9: Linear Regression

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# Roadmap

1. When Can Machines Learn?
2. Why Can Machines Learn?

**Lecture 8: Noise and Error**

learning can happen
with **target distribution** $P(y|\mathbf{x})$ and **low** $E_{\text{in}}$ **w.r.t.** $\mathbf{err}$

3. **How** Can Machines Learn?

**Lecture 9: Linear Regression**

- Linear Regression Problem
- Linear Regression Algorithm
- Generalization Issue
- Linear Regression for Binary Classification

4. How Can Machines Learn Better?

# Credit **Limit** Problem

| | |
|---|---|
| age | 23 years |
| gender | female |
| annual salary | NTD 1,000,000 |
| year in residence | 1 year |
| year in job | 0.5 year |
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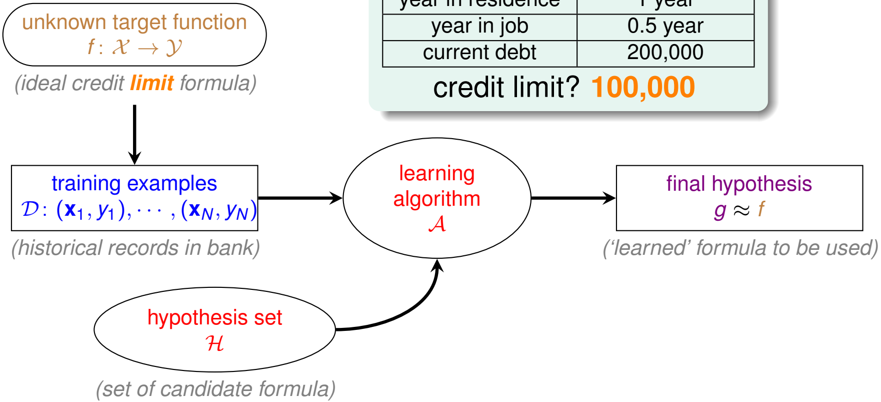

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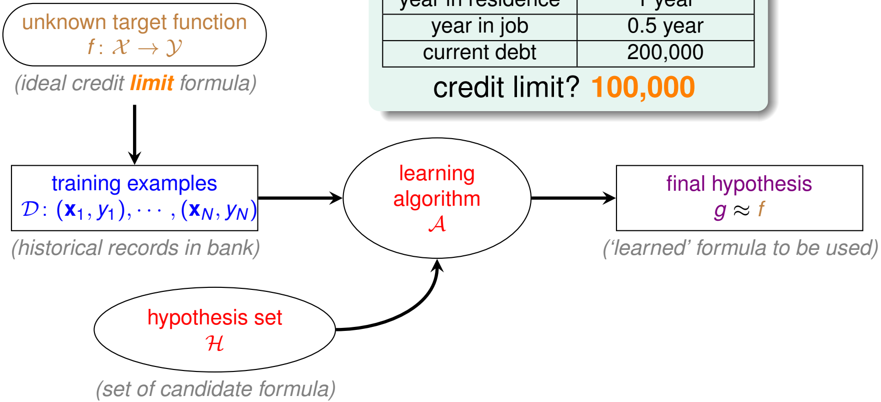


$\mathcal{Y} = \mathbb{R}$: **regression**

# Linear Regression Hypothesis

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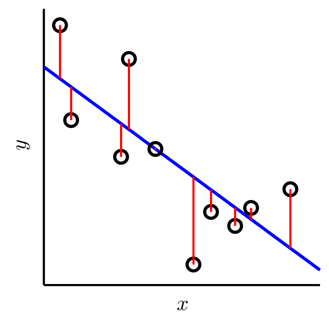
$h(\mathbf{x})$: like **perceptron**, but without the sign

# Illustration of Linear Regression

## $\mathbf{x} = (x) \in \mathbb{R}$



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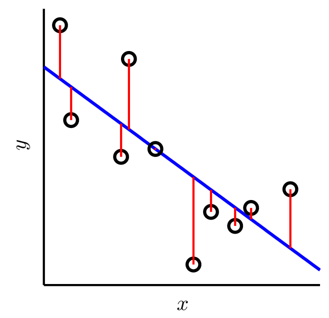
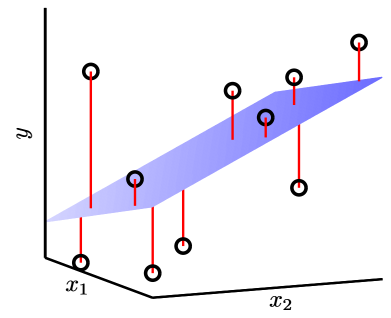



**$\mathbf{x} = (x_1, x_2) \in \mathbb{R}^2$**



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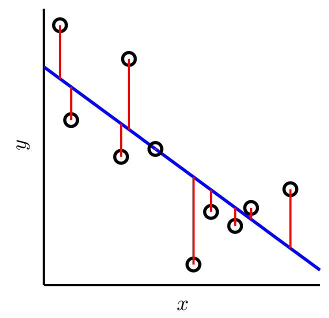


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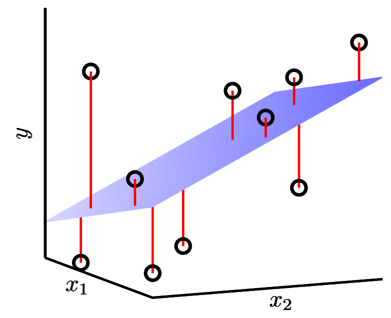


linear regression:
find lines/hyperplanes with small residuals

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popular/historical error measure:

squared error $\mathrm{err}(\hat{y}, y) = (\hat{y} - y)^2$

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$$E_{\text{out}}(\mathbf{w}) = \mathop{\mathcal{E}}_{(\mathbf{x},y)\sim P}(\mathbf{w}^T\mathbf{x} - y)^2$$

next: how to minimize $E_{\text{in}}(\mathbf{w})$?

# Fun Time

Consider using linear regression hypothesis $h(\mathbf{x}) = \mathbf{w}^T\mathbf{x}$ to predict the credit limit of customers $\mathbf{x}$. Which feature below shall have a positive weight in a **good hypothesis** for the task?

1. birth month
2. monthly income
3. current debt
4. number of credit cards owned

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**Reference Answer: ②**

Customers with higher monthly income should naturally be given a higher credit limit, which is captured by the positive weight on the 'monthly income' feature.

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$$= \frac{1}{N}\left\| \left[ \quad \right]\mathbf{w} - \left[ \quad \right] \right\|^2$$

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&= \frac{1}{N}\left\| \begin{bmatrix} --\mathbf{x}_1^T-- \\ --\mathbf{x}_2^T-- \\ \ldots \\ --\mathbf{x}_N^T-- \end{bmatrix} \mathbf{w} - \begin{bmatrix} y_1 \\ y_2 \\ \ldots \\ y_N \end{bmatrix} \right\|^2
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&= \frac{1}{N}\left\| \begin{bmatrix} - - \mathbf{x}_1^T - - \\ - - \mathbf{x}_2^T - - \\ \cdots \\ - - \mathbf{x}_N^T - - \end{bmatrix} \mathbf{w} - \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_N \end{bmatrix} \right\|^2 \\
&= \frac{1}{N}\| \underbrace{\mathrm{X}}_{N\times d+1} \underbrace{\mathbf{w}}_{d+1\times 1} - \underbrace{\mathbf{y}}_{N\times 1} \|^2
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$$

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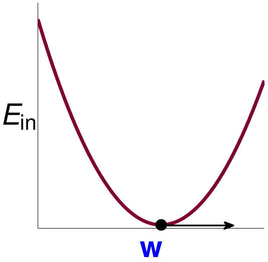


- $E_{\text{in}}(\mathbf{w})$: continuous, differentiable, **convex**

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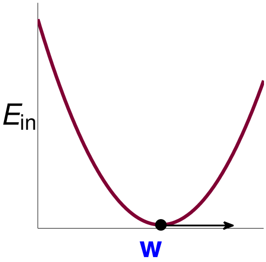


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$$\nabla E_{\text{in}}(\mathbf{w}) \equiv \begin{bmatrix} \frac{\partial E_{\text{in}}}{\partial w_0}(\mathbf{w}) \\ \frac{\partial E_{\text{in}}}{\partial w_1}(\mathbf{w}) \\ \dots \\ \frac{\partial E_{\text{in}}}{\partial w_d}(\mathbf{w}) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \dots \\ 0 \end{bmatrix}$$

—not possible to 'roll down'

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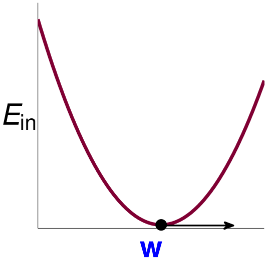


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task: find $\mathbf{w}_{\text{LIN}}$ such that $\nabla E_{\text{in}}(\mathbf{w}_{\text{LIN}}) = \mathbf{0}$

# The Gradient $\nabla E_{\text{in}}(\mathbf{w})$

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$$\nabla E_{\text{in}}(\mathbf{w}) = \frac{2}{N}\left(\mathrm{X}^T\mathrm{X}\mathbf{w} - \mathrm{X}^T\mathbf{y}\right)$$

# Optimal Linear Regression Weights

task: find $\mathbf{w}_{\text{LIN}}$ such that $\frac{2}{N}\left(\mathrm{X}^T\mathrm{X}\mathbf{w} - \mathrm{X}^T\mathbf{y}\right) = \nabla E_{\text{in}}(\mathbf{w}) = \mathbf{0}$

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- **easy!** unique solution

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by defining $\mathrm{X}^\dagger$ in other ways

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practical suggestion:

use **well-implemented † routine**

instead of $\left(\mathrm{X}^T\mathrm{X}\right)^{-1}\mathrm{X}^T$

for numerical stability when **almost-singular**

# Linear Regression Algorithm

1. from $\mathcal{D}$, construct input matrix $\mathrm{X}$ and output vector $\mathbf{y}$ by

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simple and efficient
with **good † routine**

# Fun Time

After getting $\mathbf{w}_{\text{LIN}}$, we can calculate the predictions $\hat{y}_n = \mathbf{w}_{\text{LIN}}^T \mathbf{x}_n$. If all $\hat{y}_n$ are collected in a vector $\hat{\mathbf{y}}$ similar to how we form $\mathbf{y}$, what is the matrix formula of $\hat{\mathbf{y}}$?

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## Reference Answer: ③

Note that $\hat{\mathbf{y}} = \mathrm{X}\mathbf{w}_{\text{LIN}}$. Then, a simple substitution of $\mathbf{w}_{\text{LIN}}$ reveals the answer.

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if $E_{\text{out}}(\mathbf{w}_{\text{LIN}})$ is good, **learning ‘happened’**!

# Benefit of Analytic Solution: 'Simpler-than-VC' Guarantee

$$\overline{E_{\text{in}}} = \underset{\mathcal{D} \sim P^N}{\mathcal{E}} \left\{ E_{\text{in}}(\mathbf{w}_{\text{LIN}} \text{ w.r.t. } \mathcal{D}) \right\}$$

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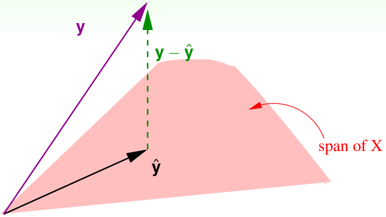
call $\mathrm{X}\mathrm{X}^\dagger$ the hat matrix $\mathrm{H}$
because it puts $\wedge$ on $\mathbf{y}$

# Geometric View of Hat Matrix

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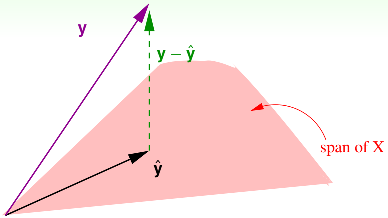


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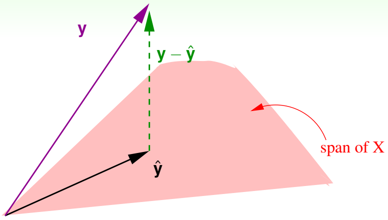


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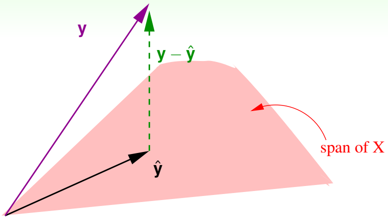


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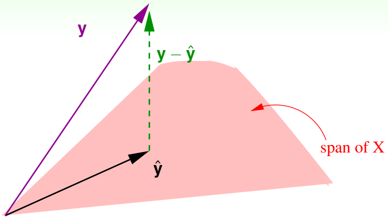


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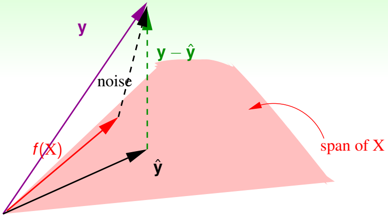
claim: $\text{trace}(\mathrm{I} - \mathrm{H}) = N - (d + 1)$. **Why? :-)**

# An Illustrative 'Proof'

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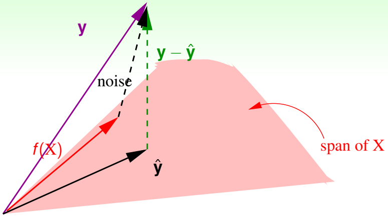


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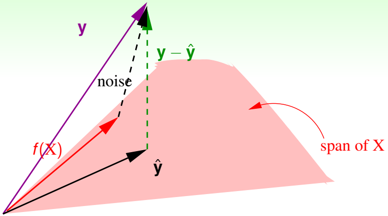


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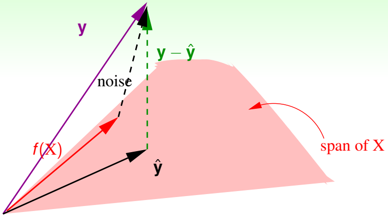


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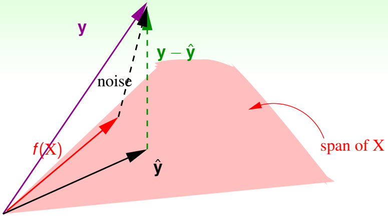


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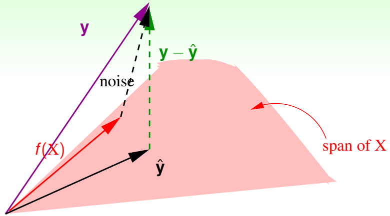


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$$\overline{E_{\text{in}}} = \sigma^2 \cdot \left(1 - \frac{d+1}{N}\right)$$
$$\overline{E_{\text{out}}} = \sigma^2 \cdot \left(1 + \frac{d+1}{N}\right)$$ **(complicated!)**

# The Learning Curve

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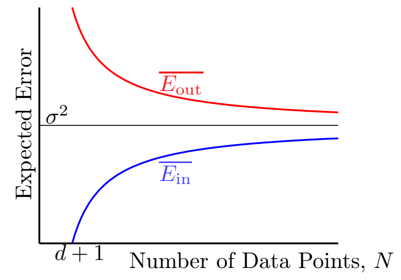

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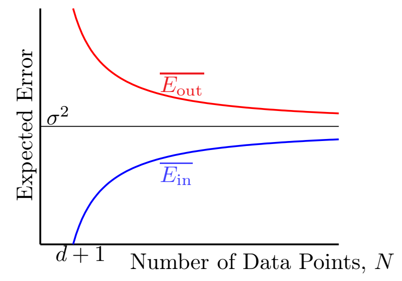


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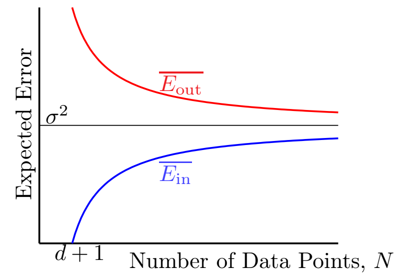


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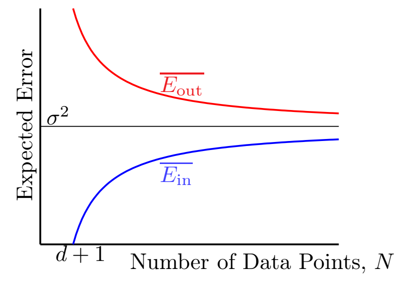


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linear regression (LinReg):
**learning 'happened'**!

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**Reference Answer: (4)**

You can conclude that (2) and (3) are true by their physical meanings! :-)

# Linear Classification vs. Linear Regression

## Linear Classification

$$\mathcal{Y} = \{-1, +1\}$$
$$h(\mathbf{x}) = \text{sign}(\mathbf{w}^T\mathbf{x})$$
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but explanation of this **heuristic**?

# Relation of Two Errors

$$\mathrm{err}_{0/1} = \left[\!\left[ \mathrm{sign}(\mathbf{w}^T\mathbf{x}) \neq y \right]\!\right] \qquad \mathrm{err}_{\mathrm{sqr}} = \left(\mathbf{w}^T\mathbf{x} - y\right)^2$$

# Relation of Two Errors

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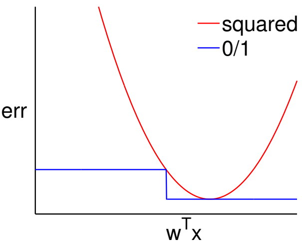

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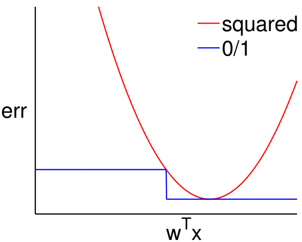
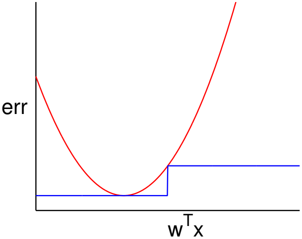



## desired $y = -1$



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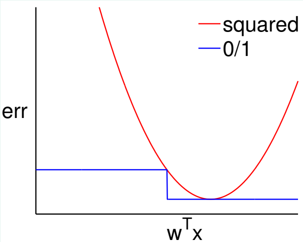


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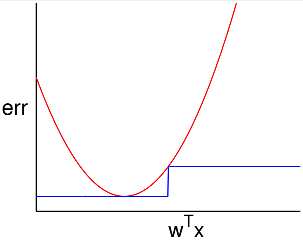


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$\mathbf{w}_{\text{LIN}}$: useful baseline classifier,
or as **initial PLA/pocket vector**

# Fun Time

Which of the following functions are upper bounds of the pointwise 0/1 error $[\![\text{sign}(\mathbf{w}^T\mathbf{x}) \neq y]\!]$ for $y \in \{-1, +1\}$?

1. $\exp(-y\mathbf{w}^T\mathbf{x})$
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## Reference Answer: ④

Plot the curves and you'll see. Thus, all three can be used for binary classification. In fact, all three functions connect to very important algorithms in machine learning and we will discuss one of them soon in the next lecture.

**Stay tuned. :-)**

# Summary

1. When Can Machines Learn?
2. Why Can Machines Learn?

## Lecture 8: Noise and Error

3. **How** Can Machines Learn?

## Lecture 9: Linear Regression

- Linear Regression Problem
  **use hyperplanes to approximate real values**
- Linear Regression Algorithm
  **analytic solution with pseudo-inverse**
- Generalization Issue
  $E_{\text{out}} - E_{\text{in}} \approx \frac{2(d+1)}{N}$ **on average**
- Linear Regression for Binary Classification
  **0/1 error $\leq$ squared error**

- **next: binary classification, regression, and then?**

4. How Can Machines Learn Better?