

Supervised Learning

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Adopted from Prof. Simon Prince

Artificial intelligence

```
graph TD; AI[Artificial intelligence] --> ML[Machine learning]; ML --> SL[Supervised learning]; ML --> UL[Unsupervised learning]; ML --> RL[Reinforcement learning]; SL --- DL[Deep learning]; UL --- DL; RL --- DL;
```

Machine learning

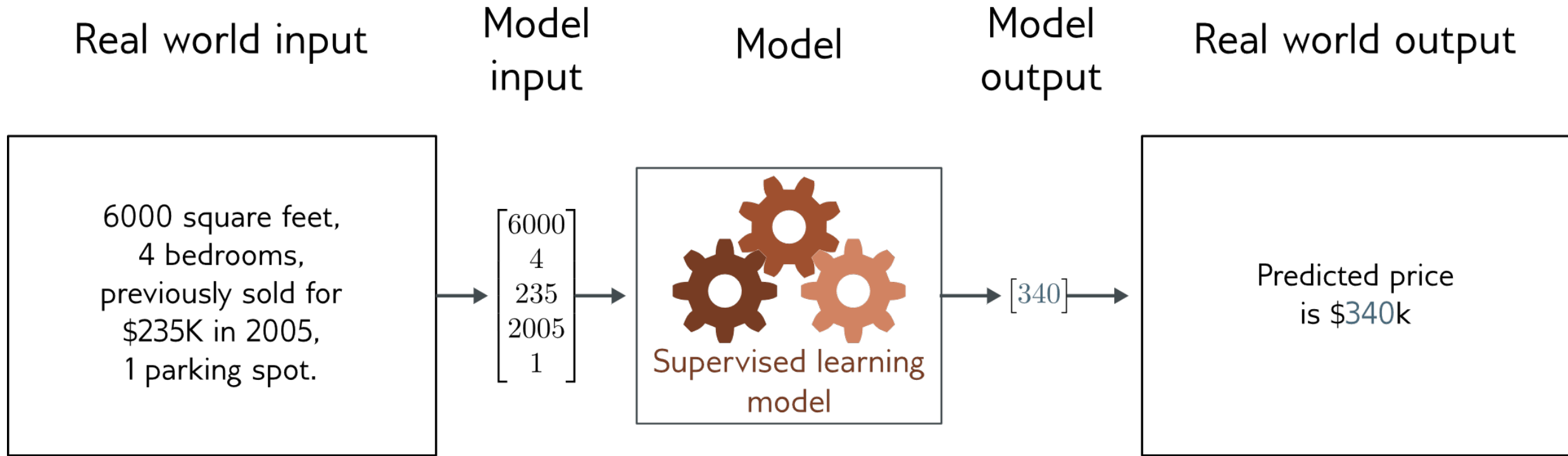
Supervised
learning

Unsupervised
learning

Reinforcement
learning

Deep learning

Regression



- Univariate regression problem (one output, real value)

Supervised learning

- Overview
- Notation
 - Model
 - Loss function
 - Training
 - Testing
- 1D Linear regression example
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- Where are we going?

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Supervised learning overview

- **Supervised learning model** = mapping from one or more inputs to one or more outputs
- Model is a mathematical equation
- Computing the inputs from the outputs = **inference**

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- Example:
 - Input is age and milage of secondhand Toyota Prius
 - Output is estimated price of car

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Supervised learning overview

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- Model is a family of equations
- Computing the inputs from the outputs = **inference**
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- Parameters affect outcome of equation
- **Training** a model = finding parameters that predict outputs “well” from inputs for a **training dataset** of input/output pairs

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Notation:

- Input:

x



Variables always Roman letters

- Output:

y

- Model:

y = **f**[**x**]



Functions always square brackets

Normal = returns scalar

Bold = returns vector

Capital Bold = returns matrix

Notation example:

- Input:

$$\mathbf{x} = \begin{bmatrix} \text{age} \\ \text{mileage} \end{bmatrix}$$

← Structured or
tabular data

- Output:

$$y = [\text{price}]$$

- Model:

$$y = f[\mathbf{x}]$$

Model

- Parameters:

ϕ

Parameters always
Greek letters

- Model :

$$y = \mathbf{f}[\mathbf{x}, \phi]$$

Loss function

- Training dataset of I pairs of input/output examples:

$$\{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^I$$

- Loss function or cost function measures how bad model is:

$$L \left[\underbrace{\phi, f[\mathbf{x}, \phi]}_{\text{model}}, \underbrace{\{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^I}_{\text{train data}} \right]$$

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or for short:

$$L[\phi]$$

← Returns a scalar that is smaller when model maps inputs to outputs better

Training

- Loss function:

$$L[\phi]$$

← Returns a scalar that is smaller when model maps inputs to outputs better

- Find the parameters that minimize the loss:

$$\hat{\phi} = \operatorname{argmin}_{\phi} [L[\phi]]$$

Testing

- To test the model, run on a separate **test dataset** of input / output pairs
- See how well it **generalizes** to new data

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Example: 1D Linear regression model

- Model:

$$\begin{aligned} y &= f[x, \phi] \\ &= \phi_0 + \phi_1 x \end{aligned}$$

- Parameters

$$\phi = \begin{bmatrix} \phi_0 \\ \phi_1 \end{bmatrix}$$

← y-offset

← slope

Example: 1D Linear regression model

- Model:

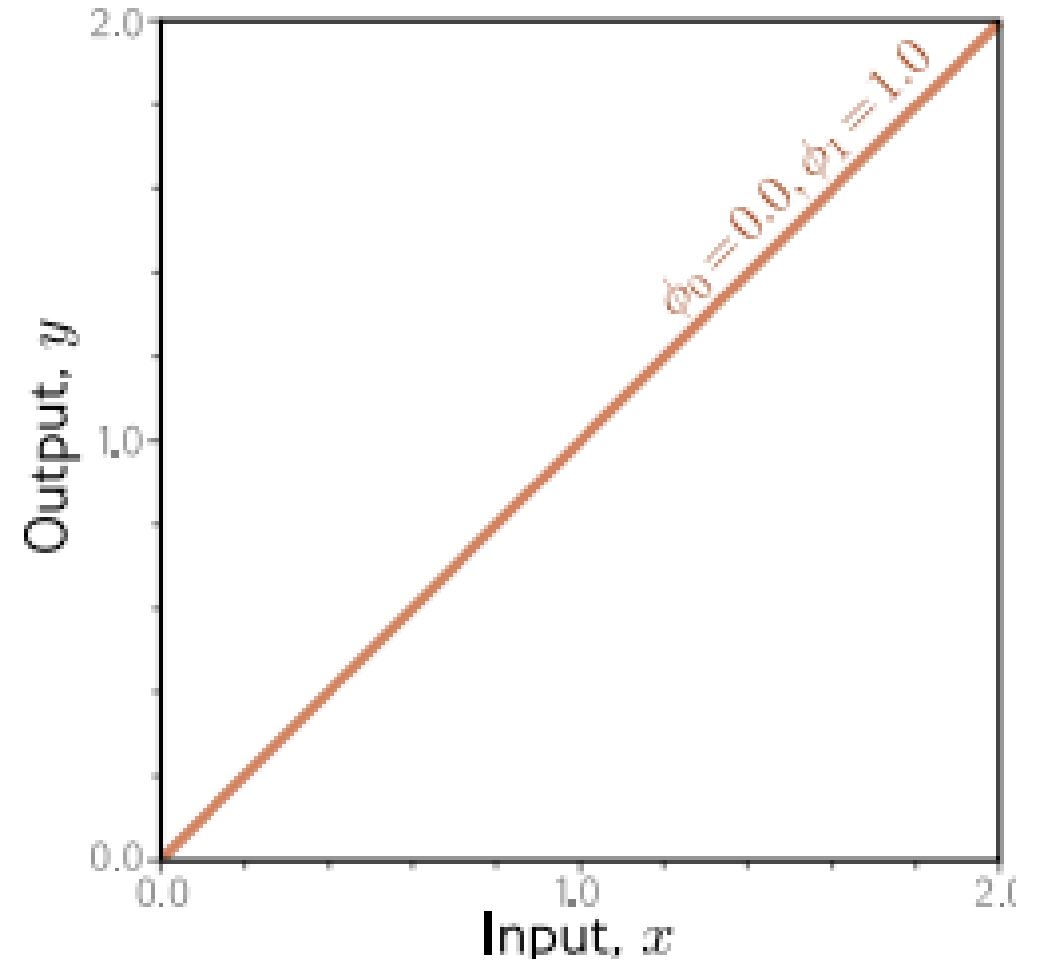
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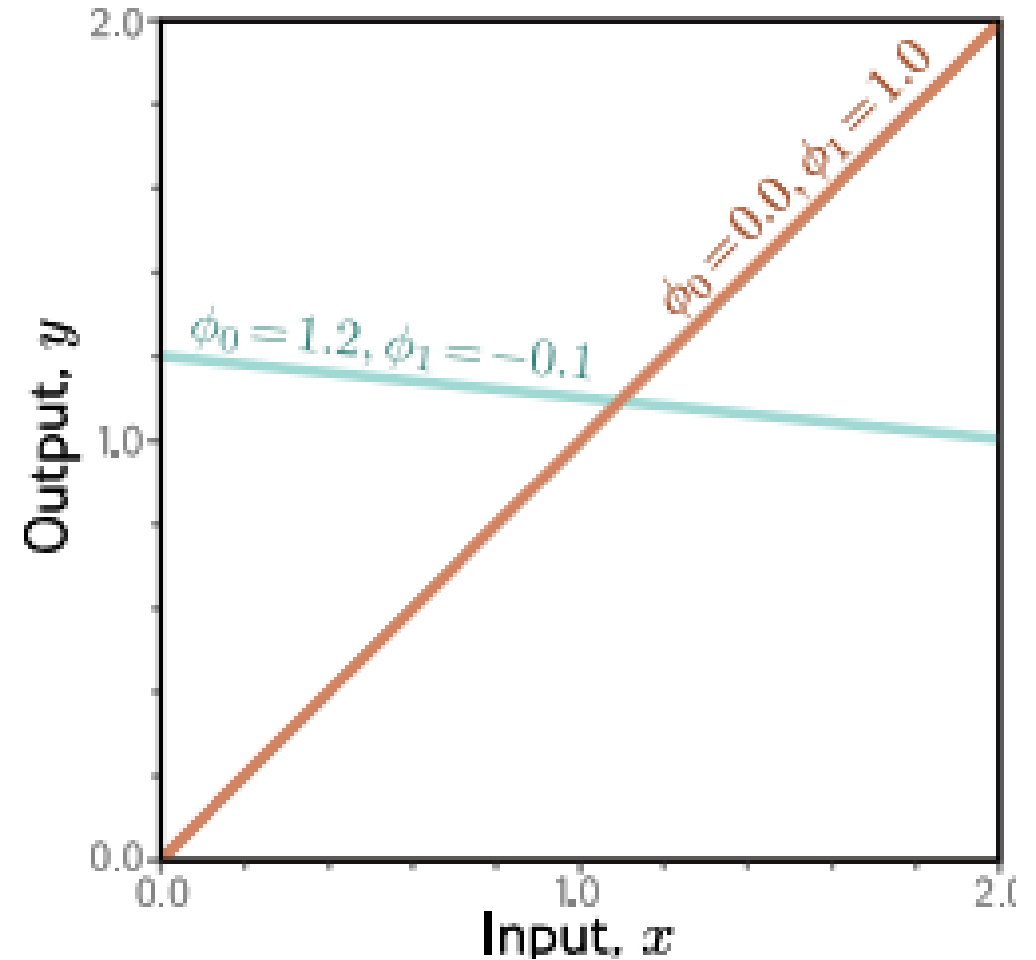
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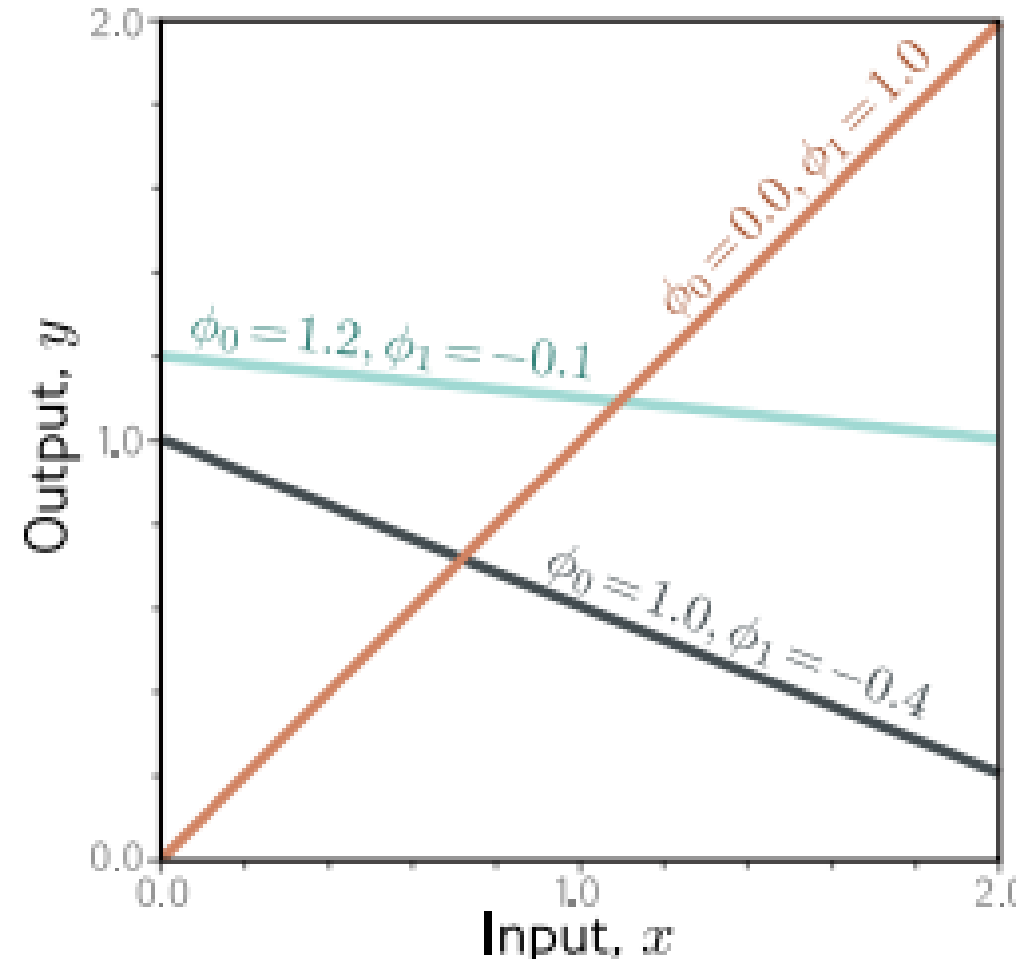
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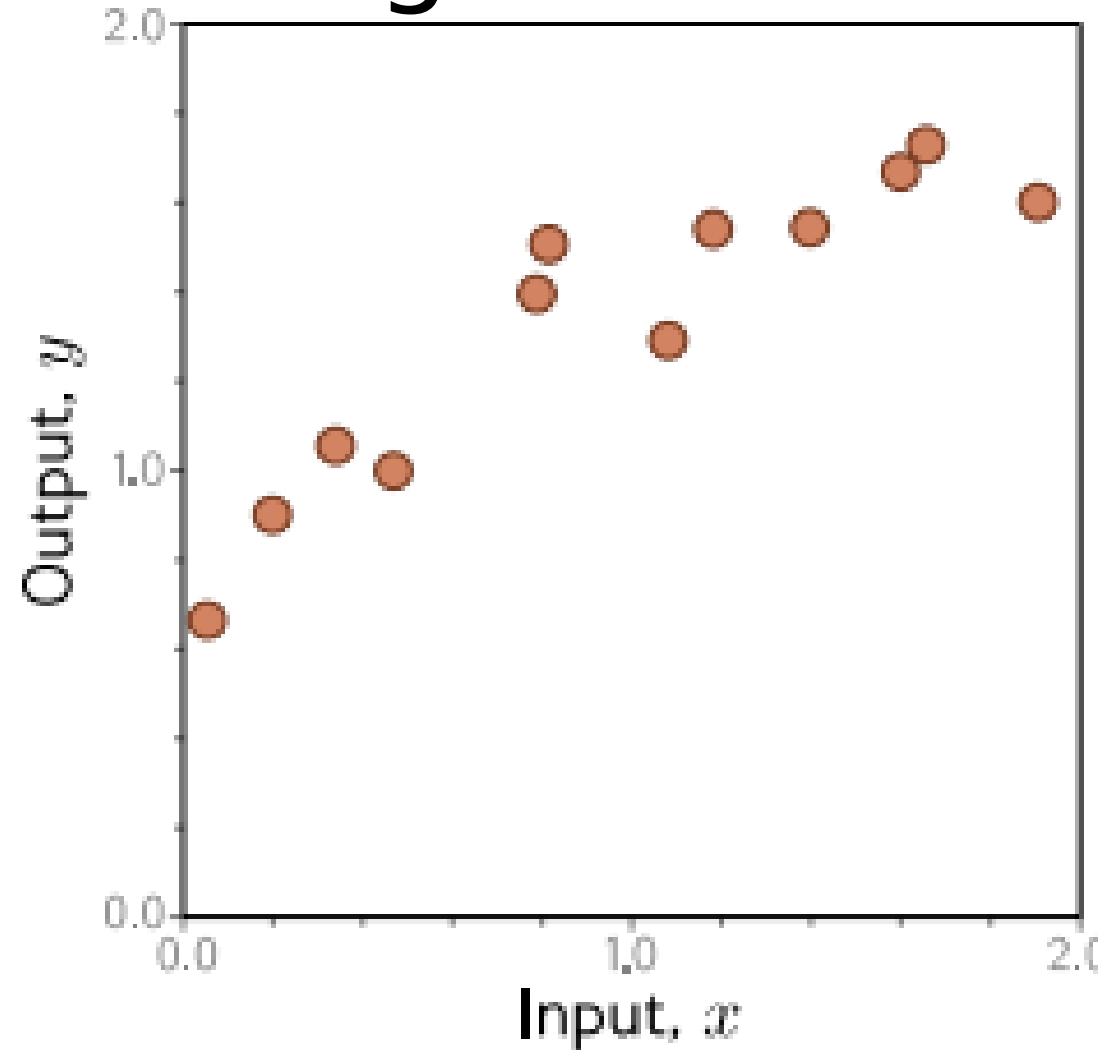
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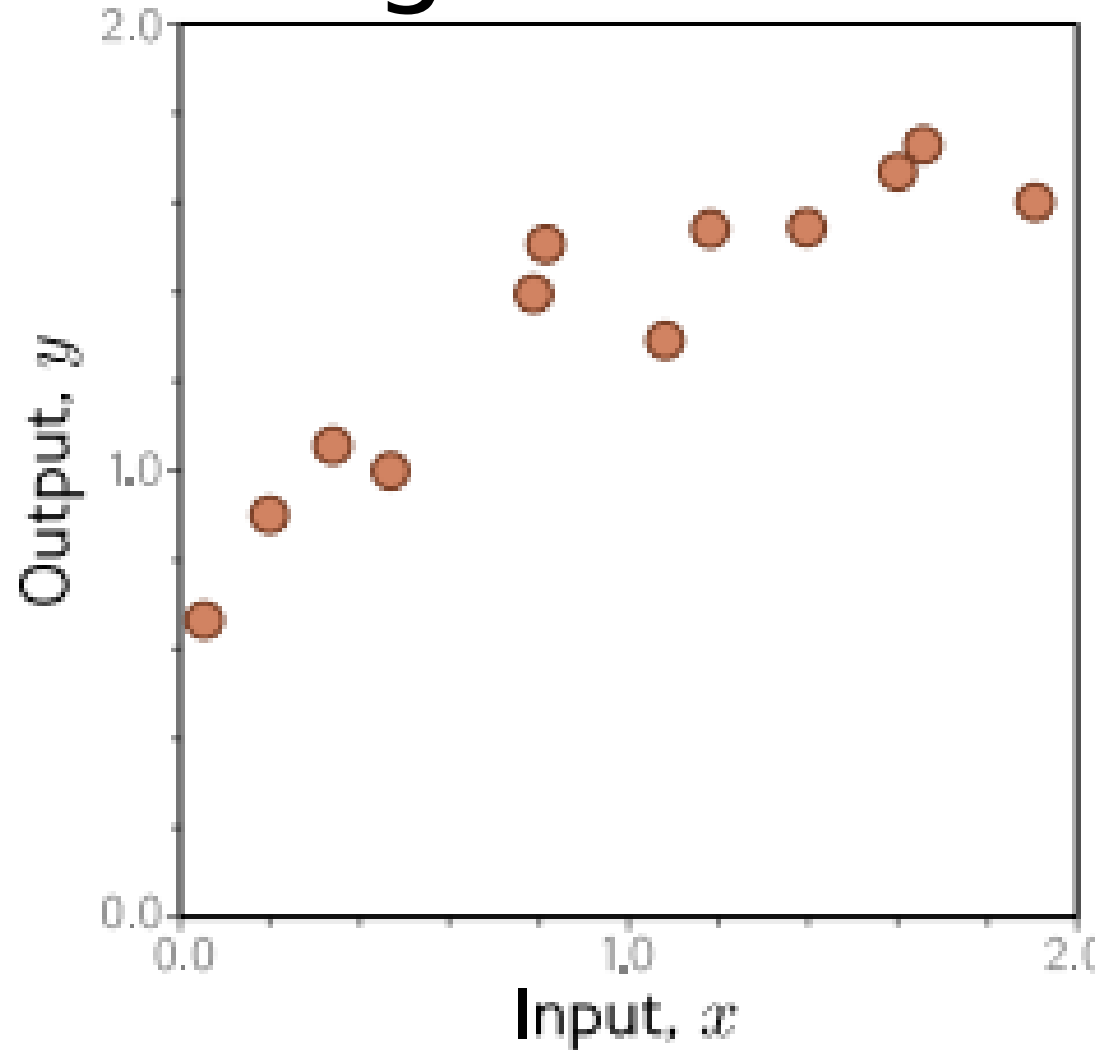
← slope



Example: 1D Linear regression training data



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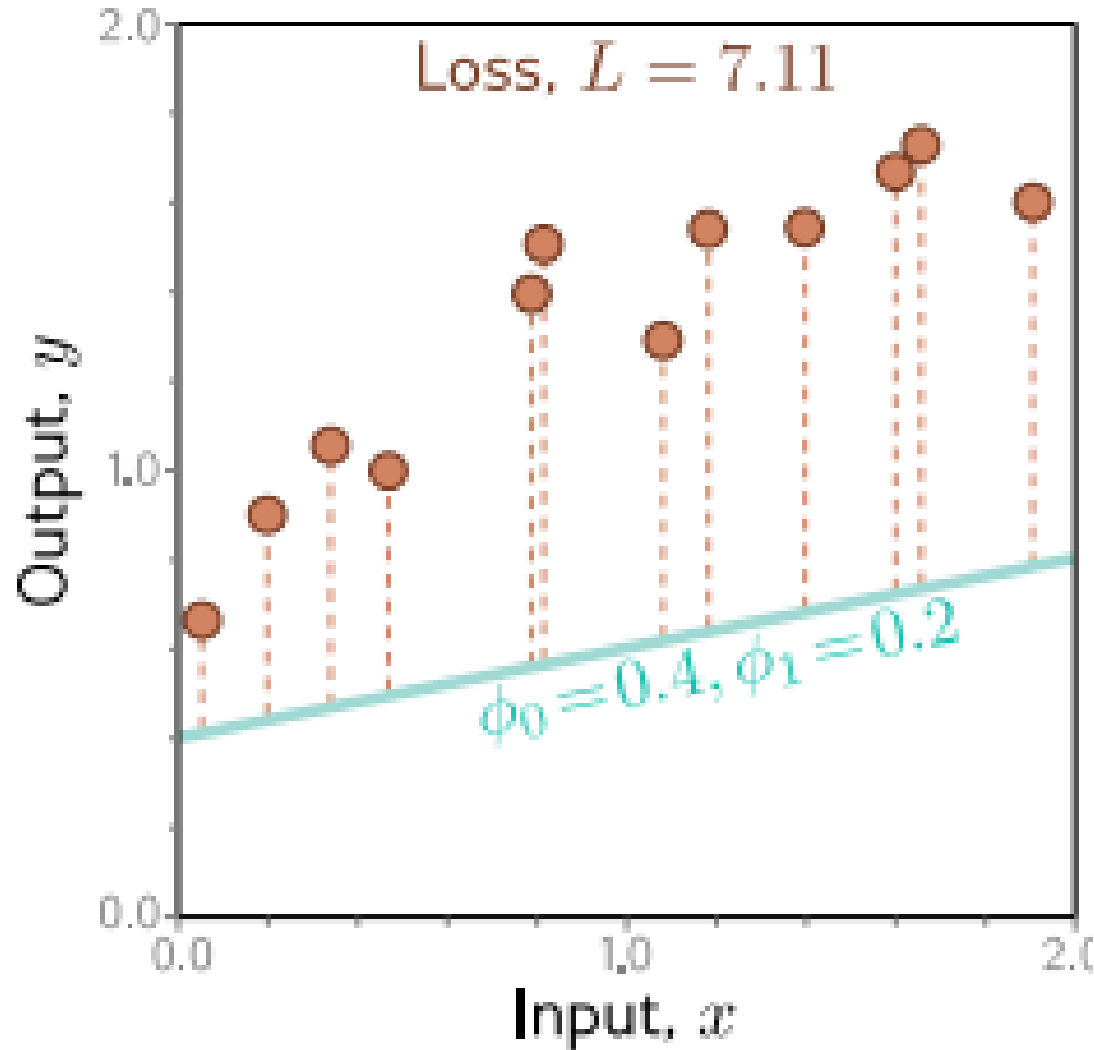


Loss function:

$$\begin{aligned} L[\phi] &= \sum_{i=1}^I (f[x_i, \phi] - y_i)^2 \\ &= \sum_{i=1}^I (\phi_0 + \phi_1 x_i - y_i)^2 \end{aligned}$$

“Least squares loss function”

Example: 1D Linear regression loss function

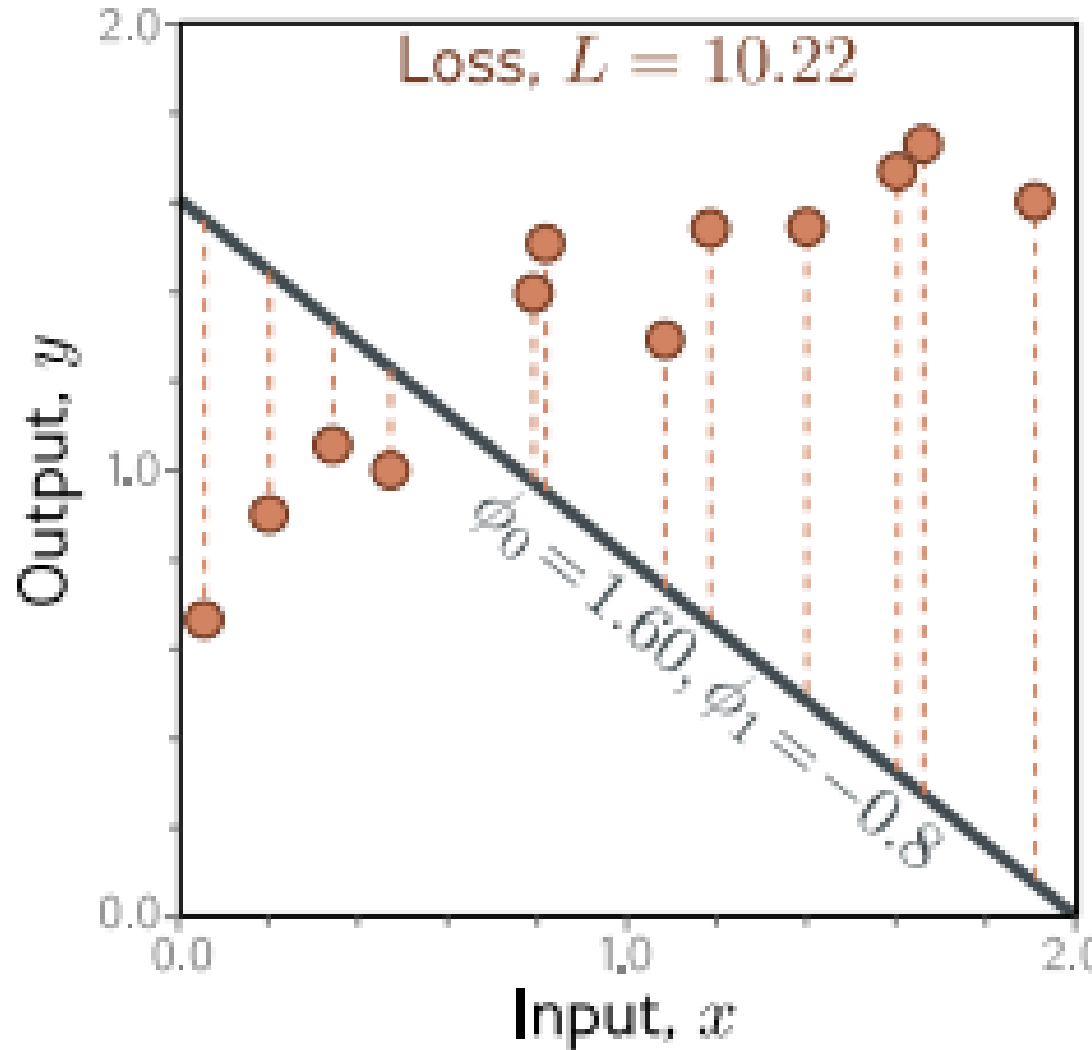


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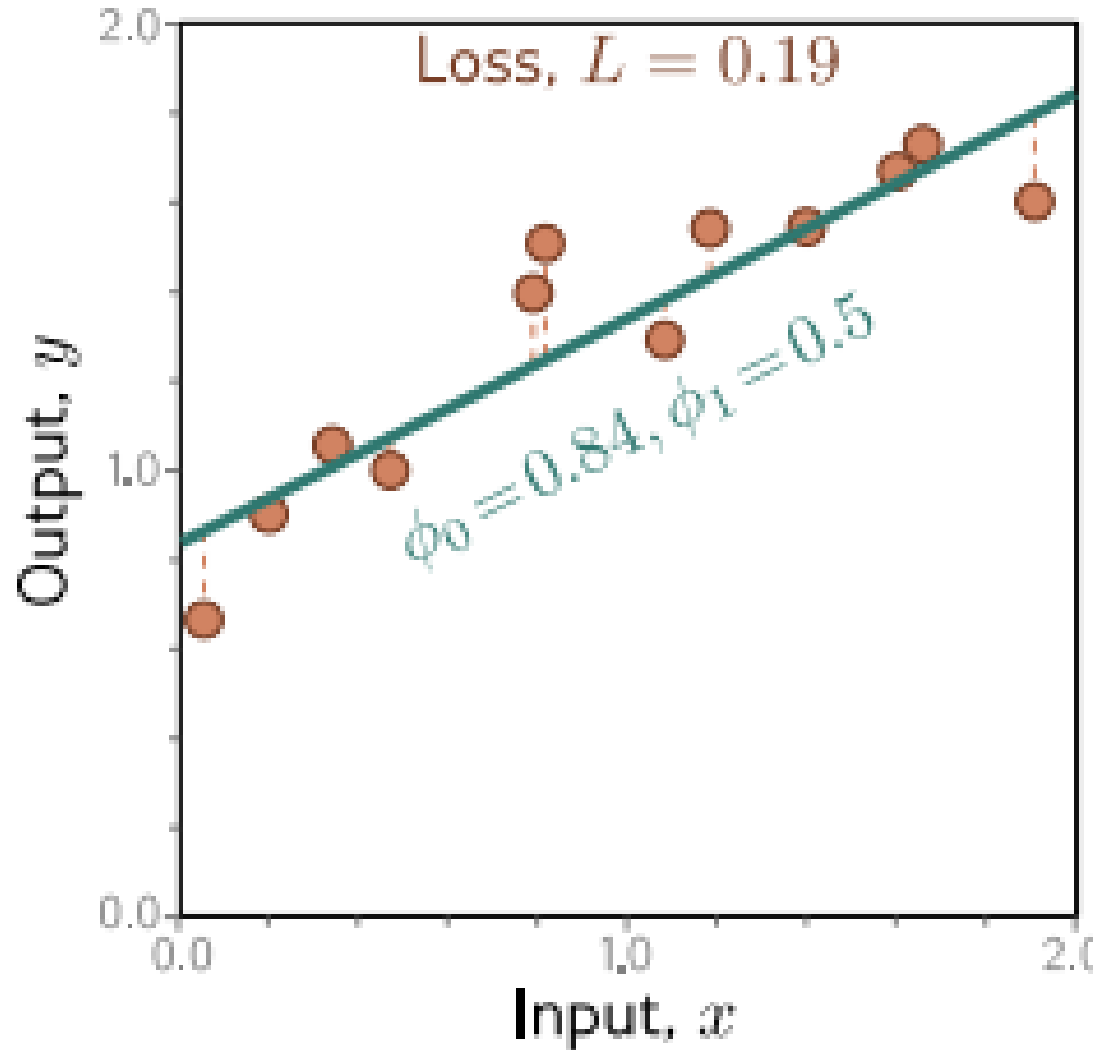


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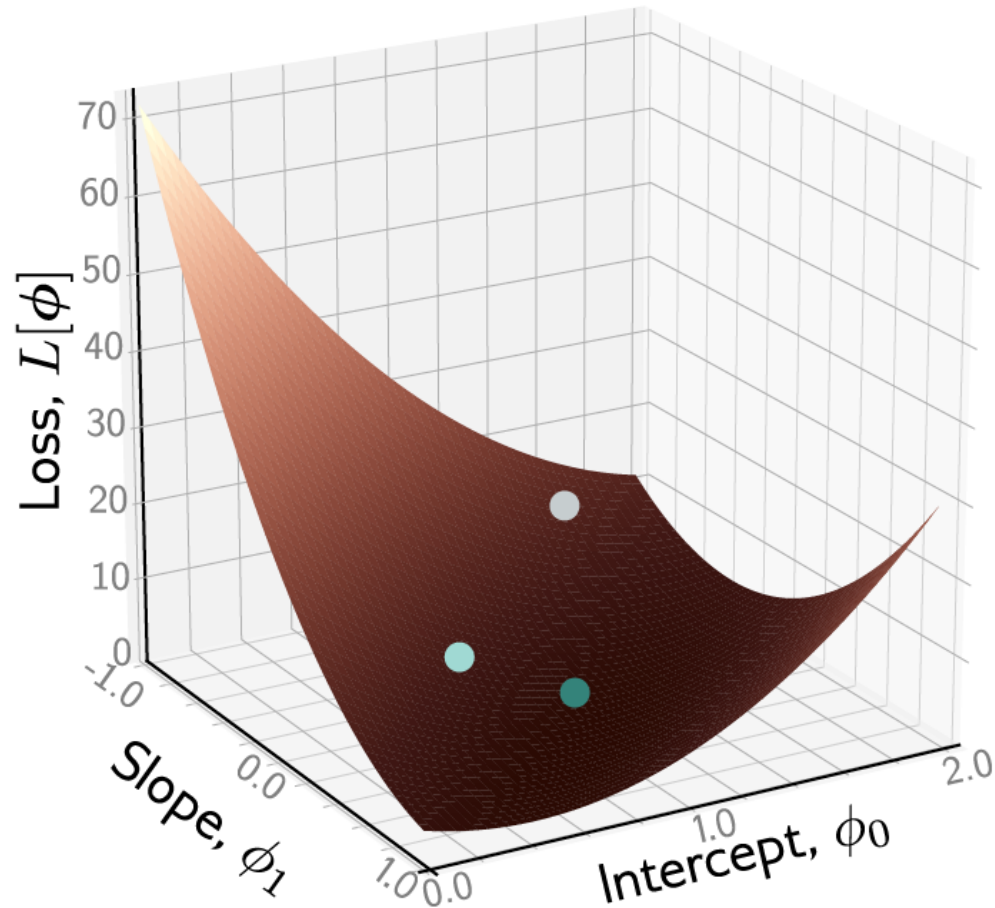


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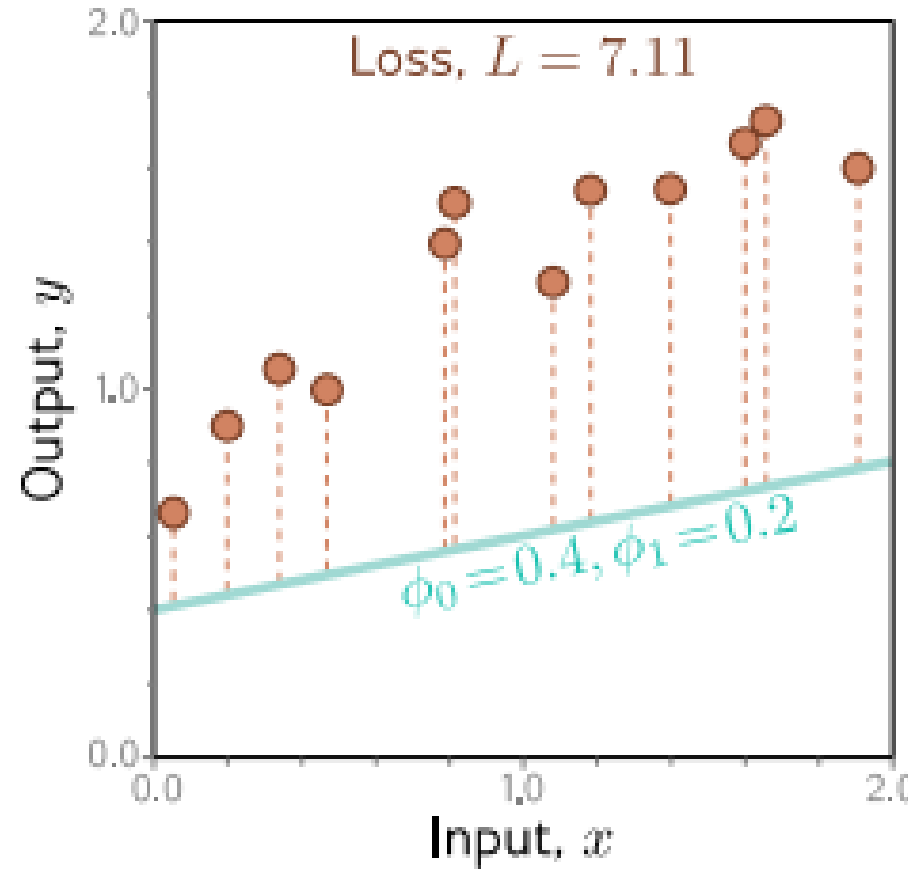
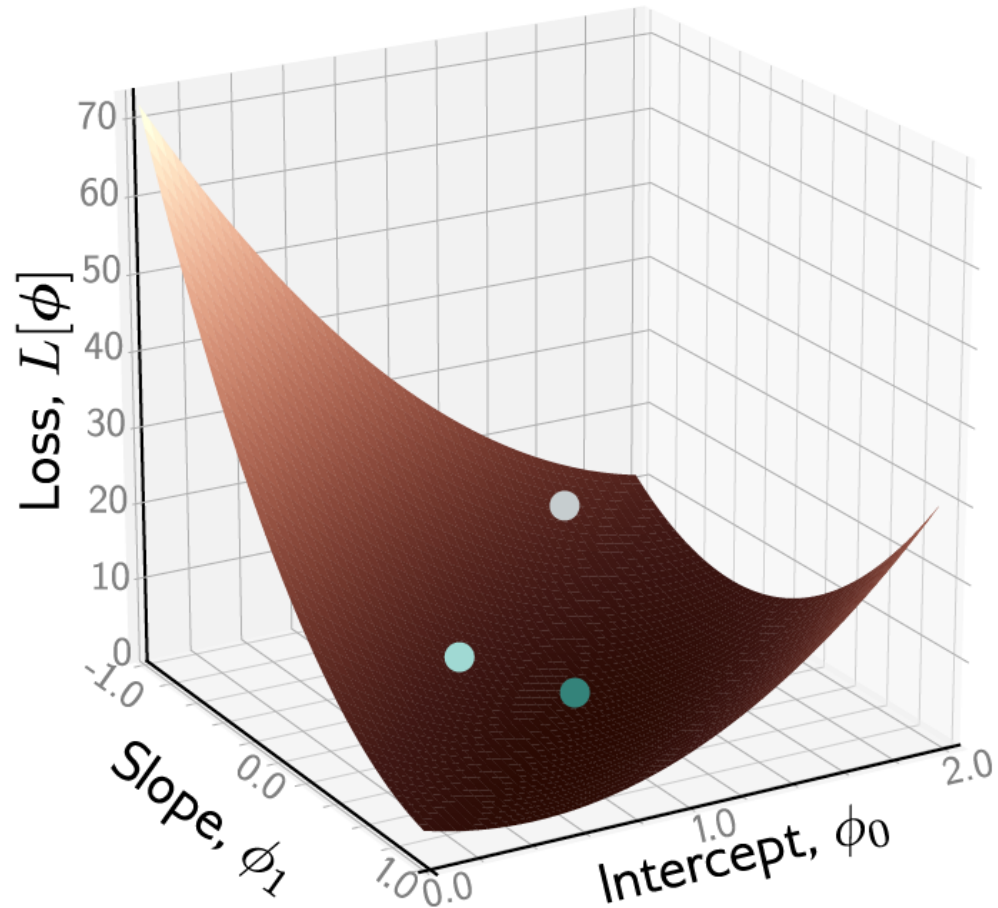


Loss function:

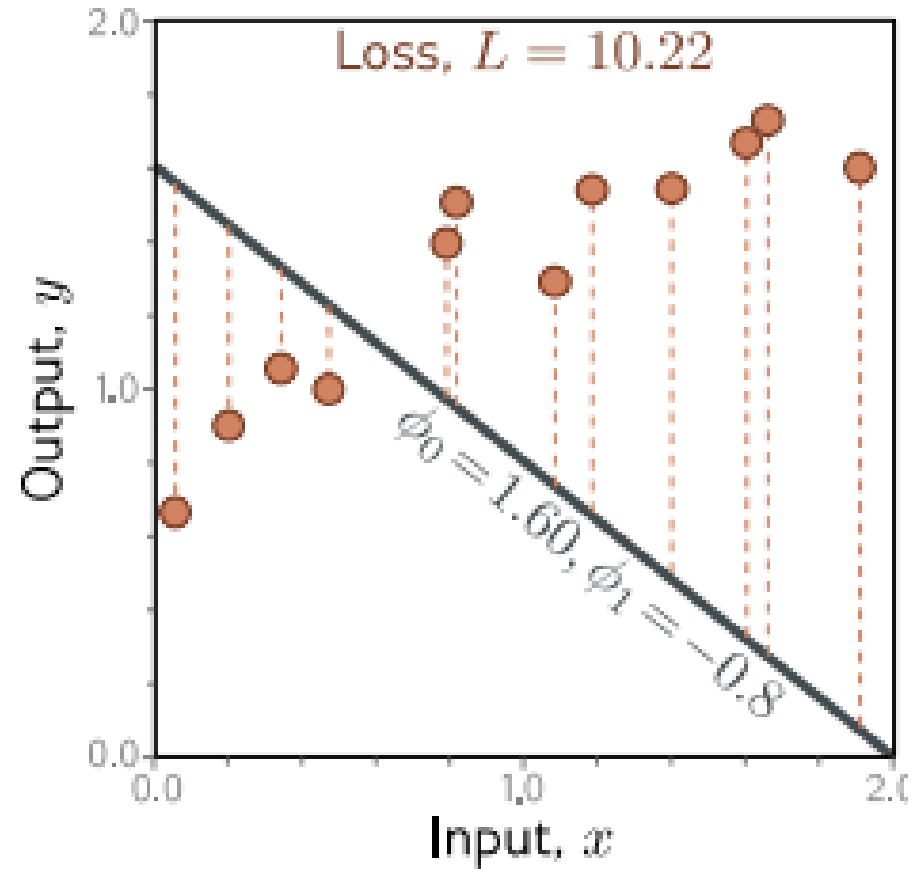
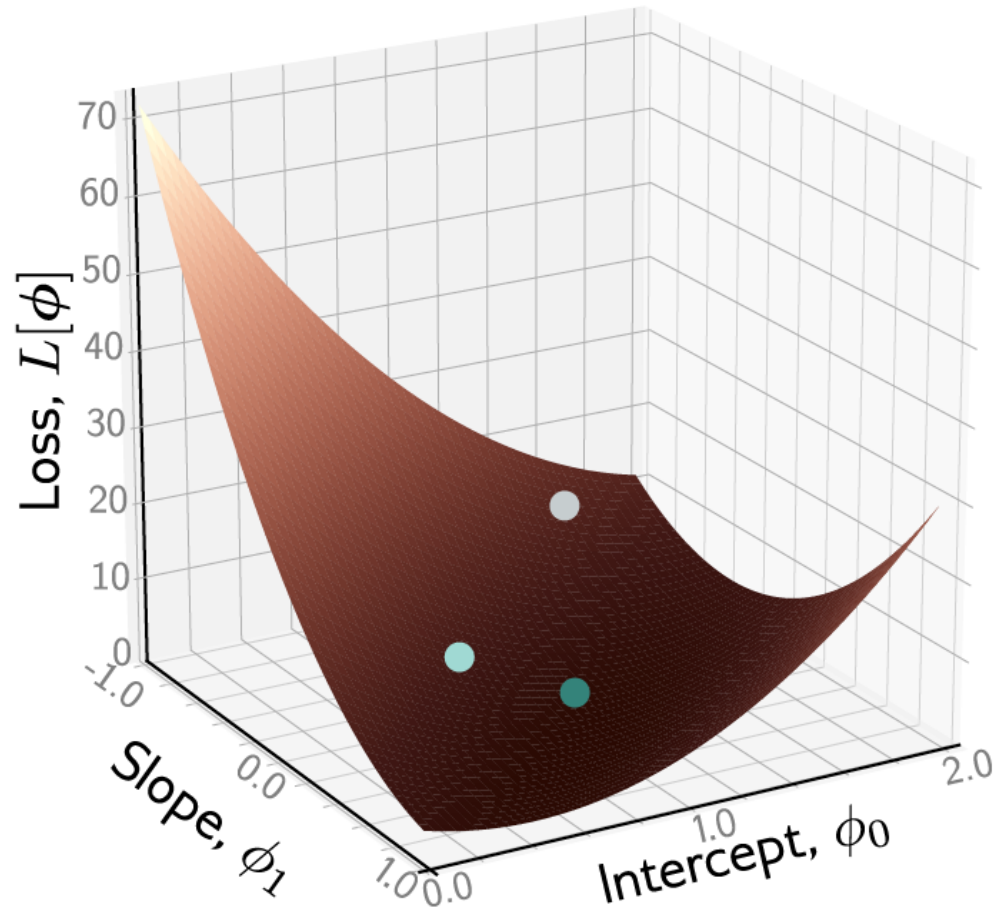
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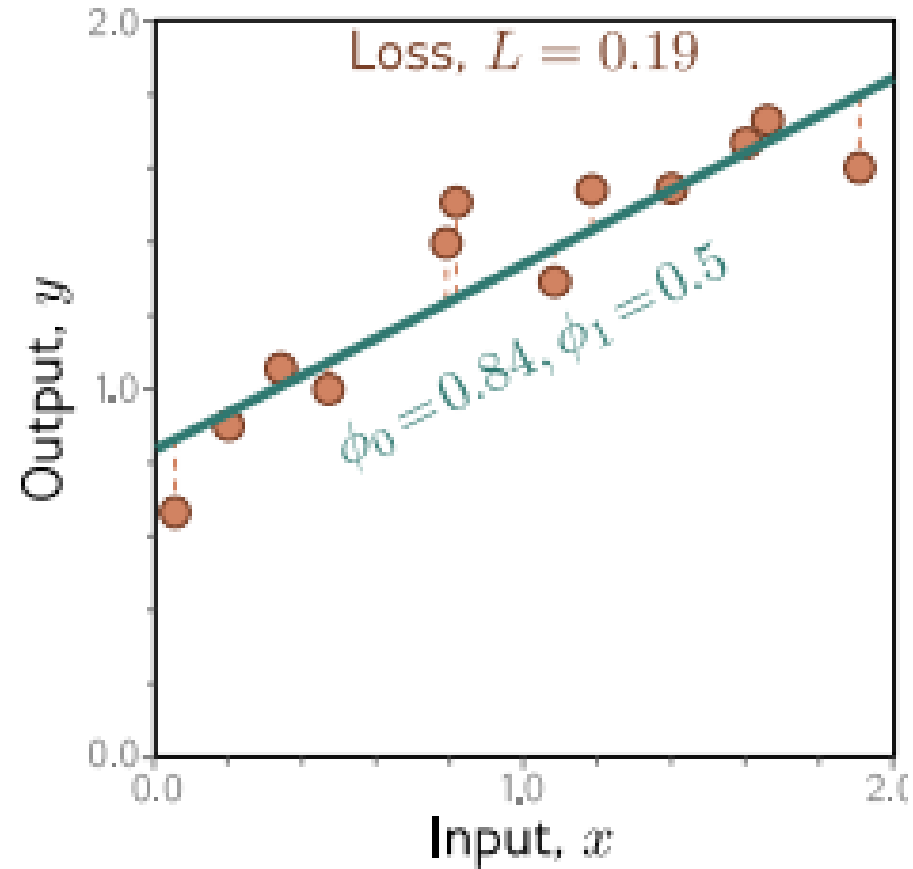
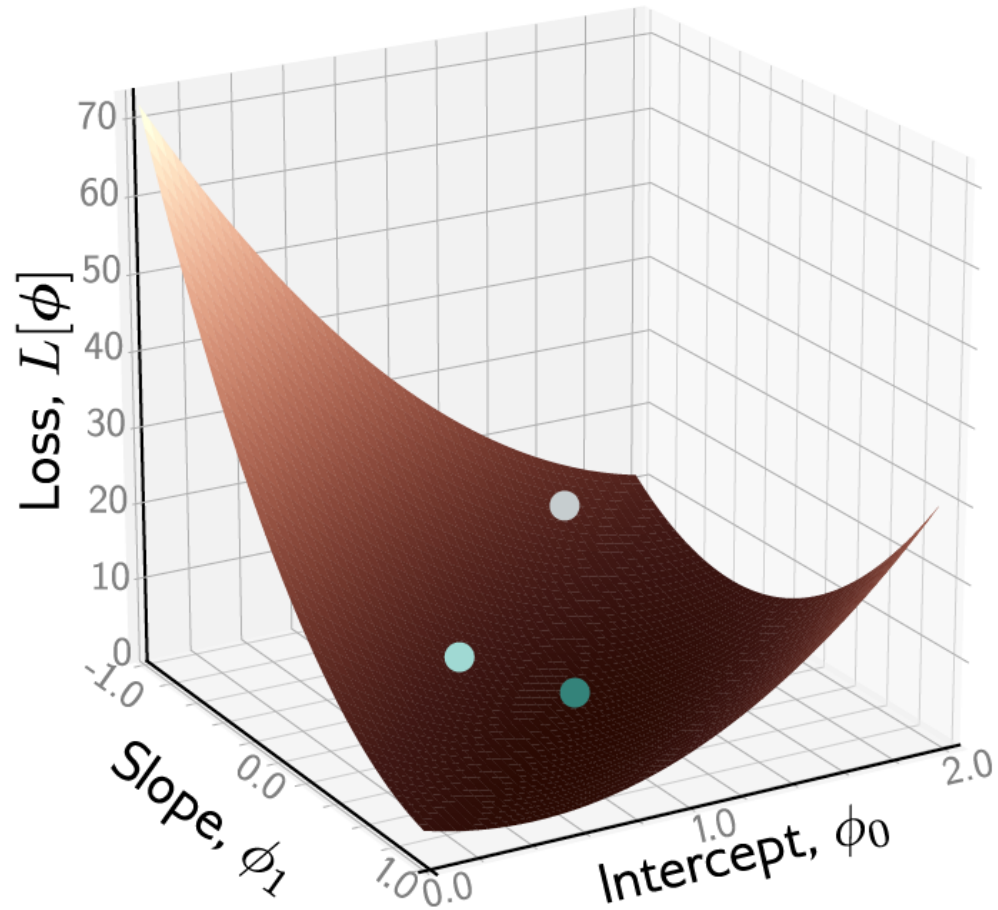
Example: 1D Linear regression loss function



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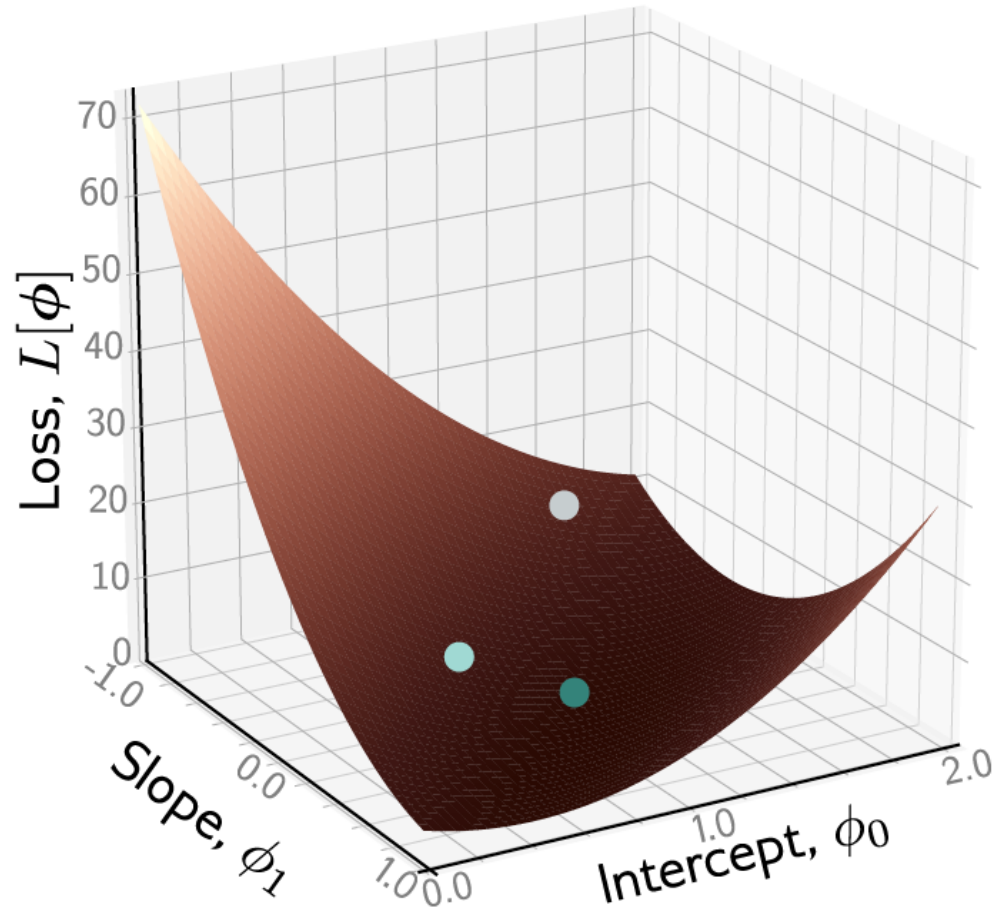


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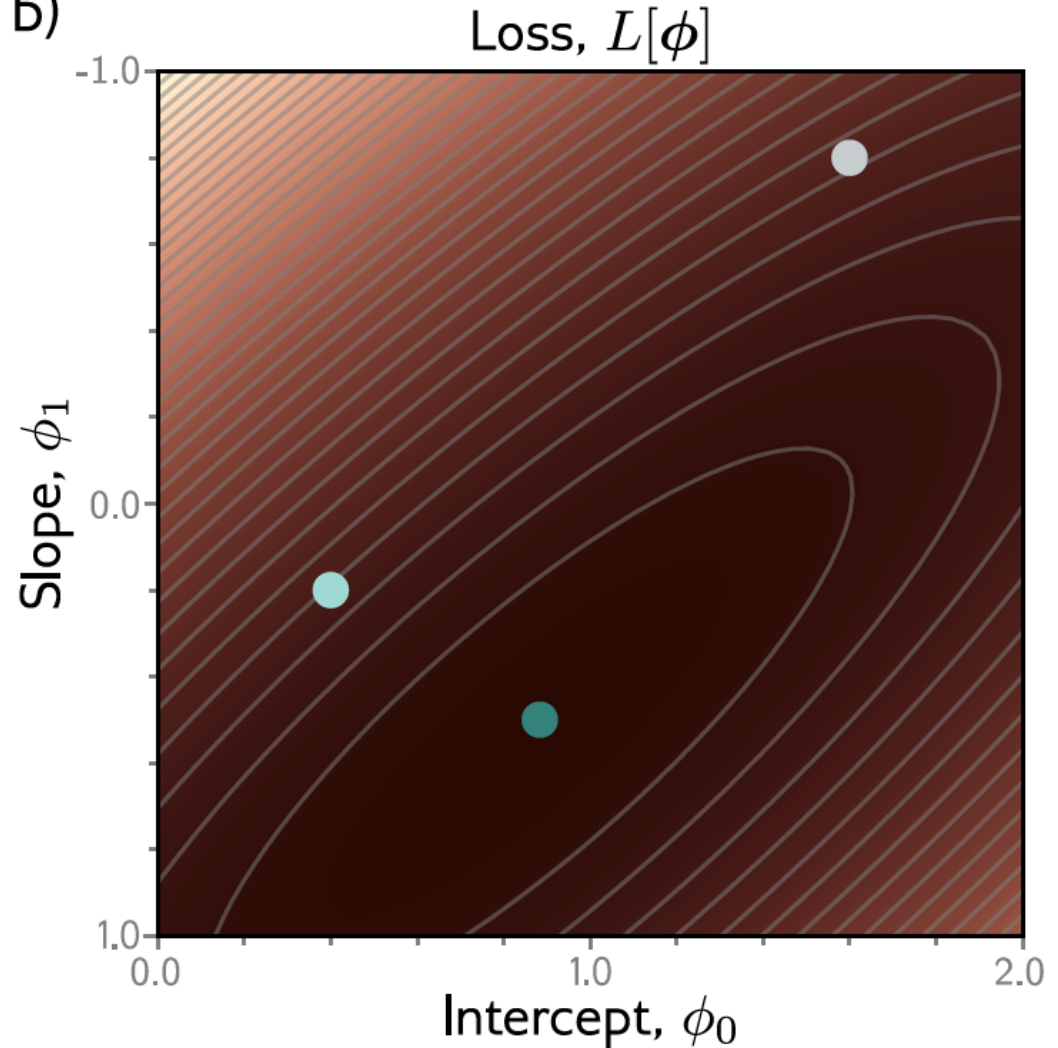


Example: 1D Linear regression loss function

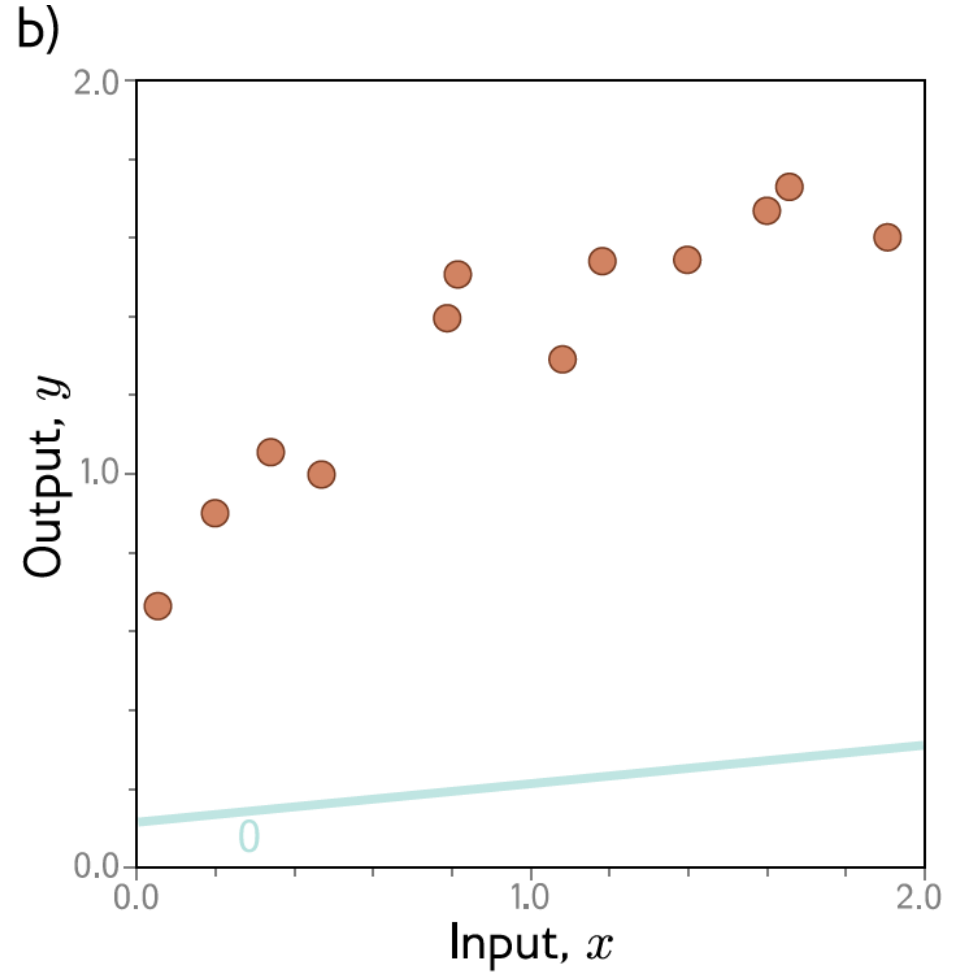
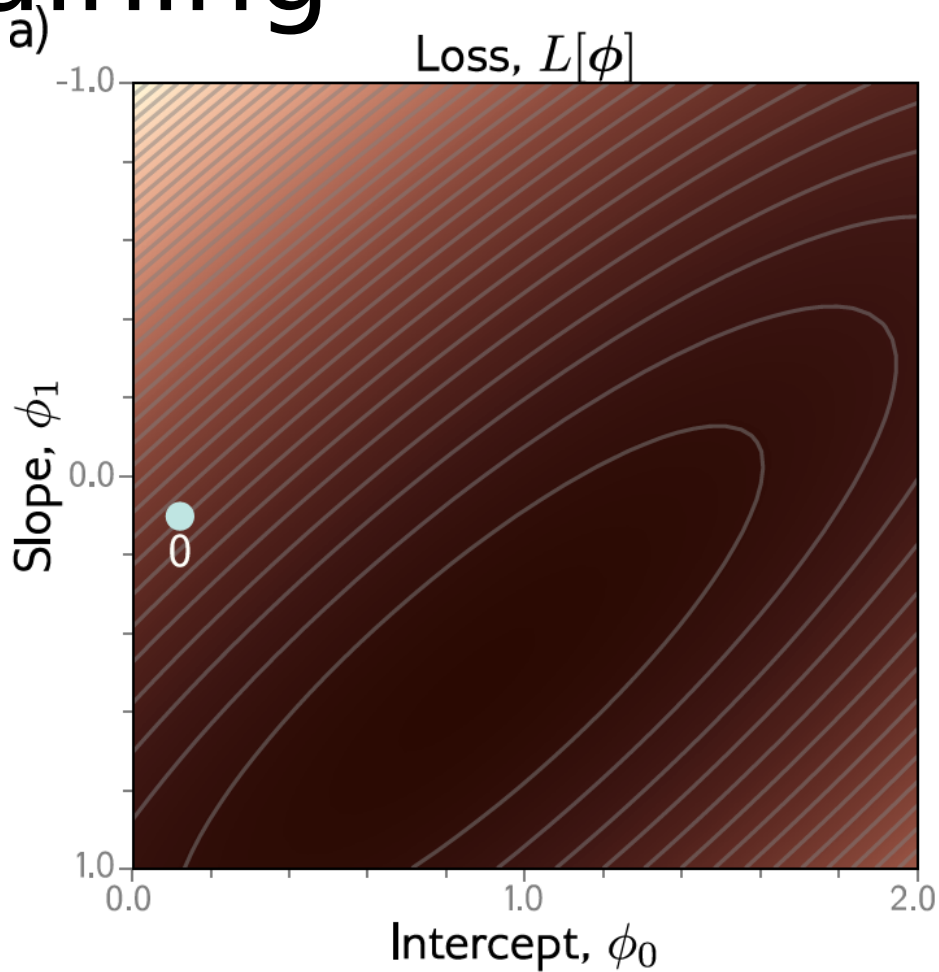
a)



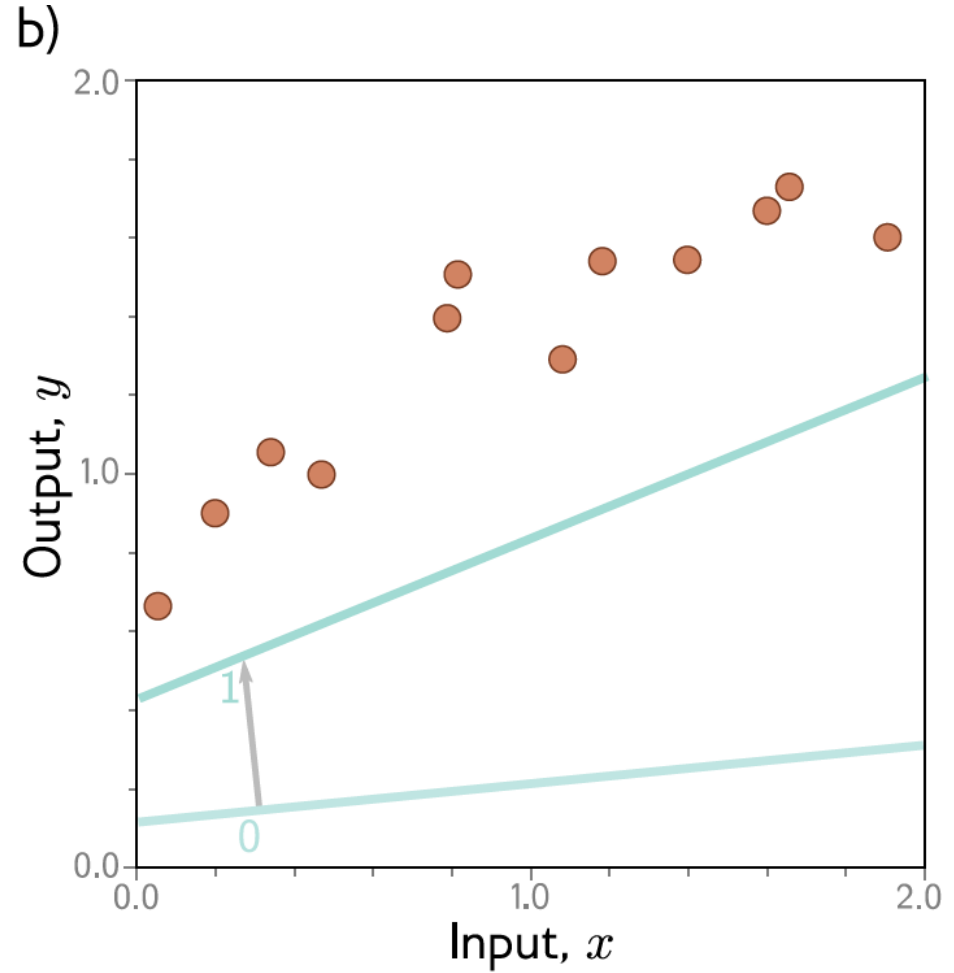
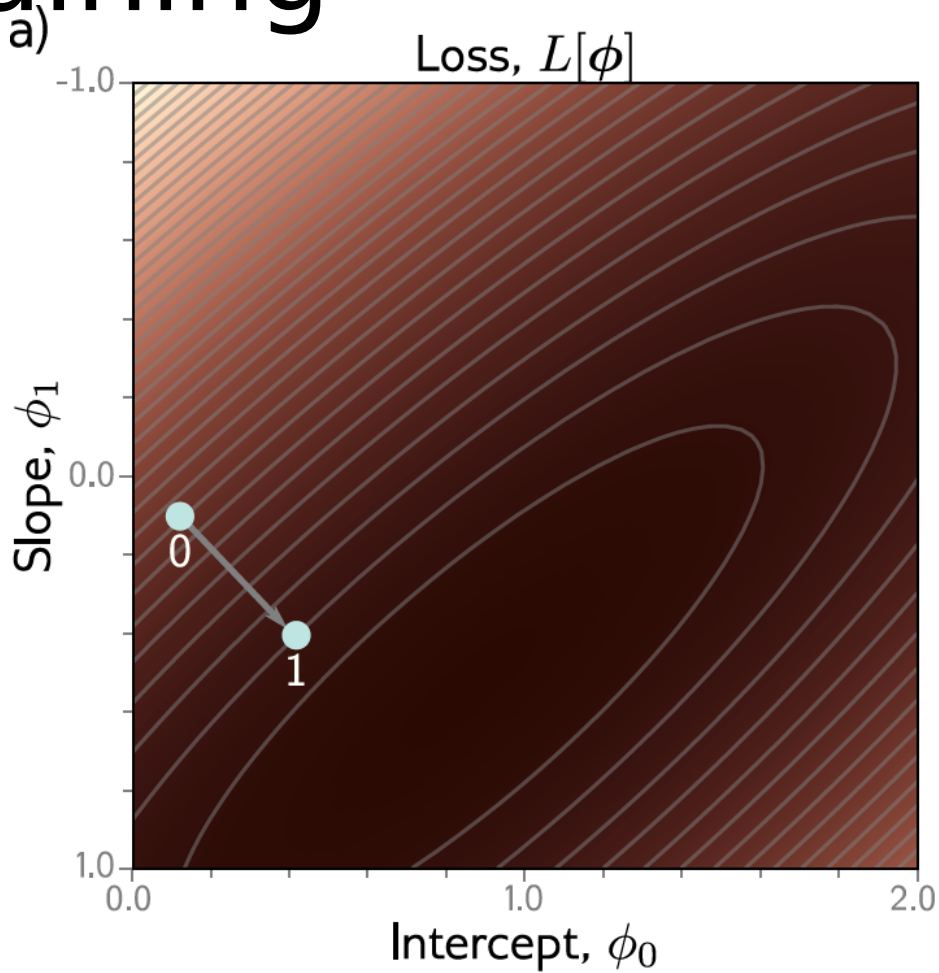
b)



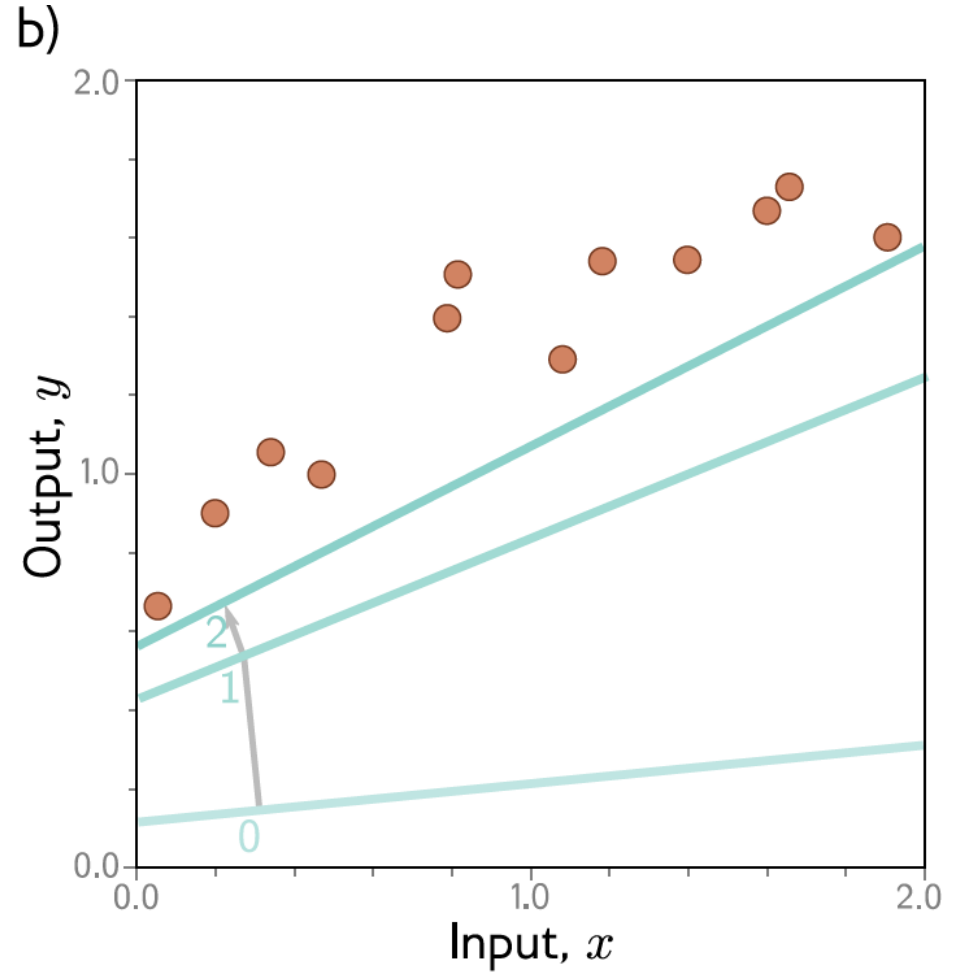
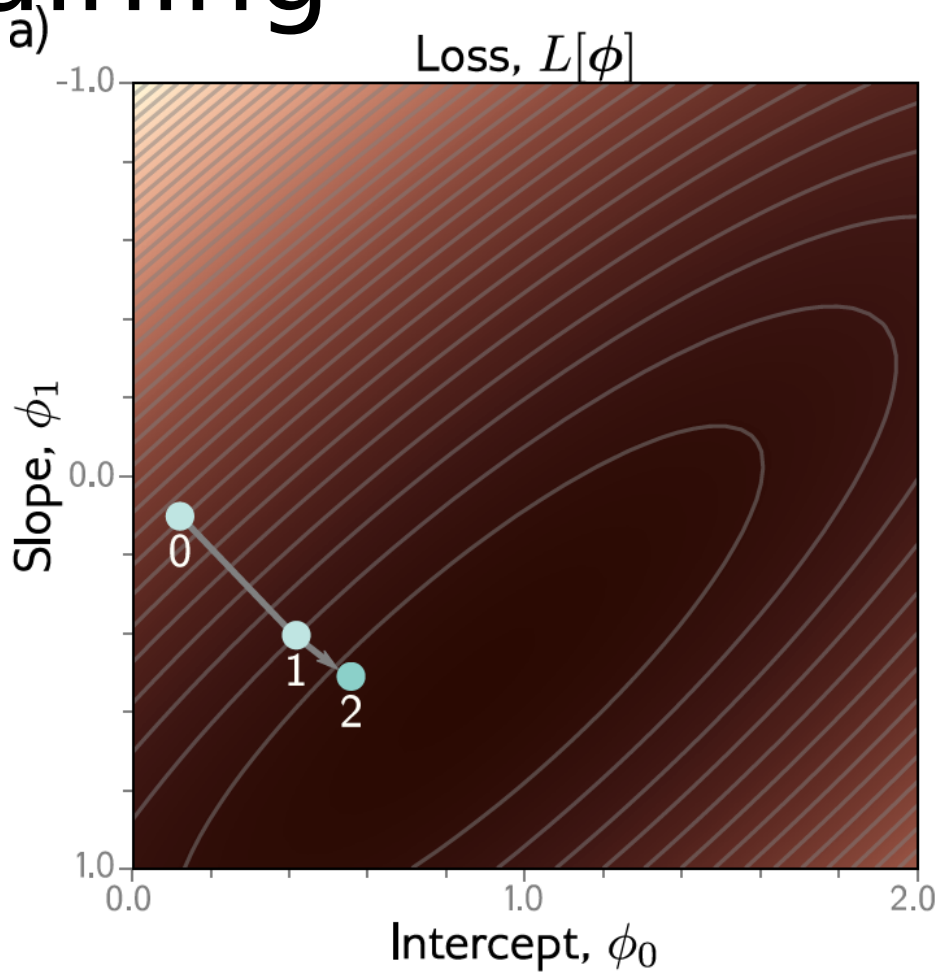
Example: 1D Linear regression training



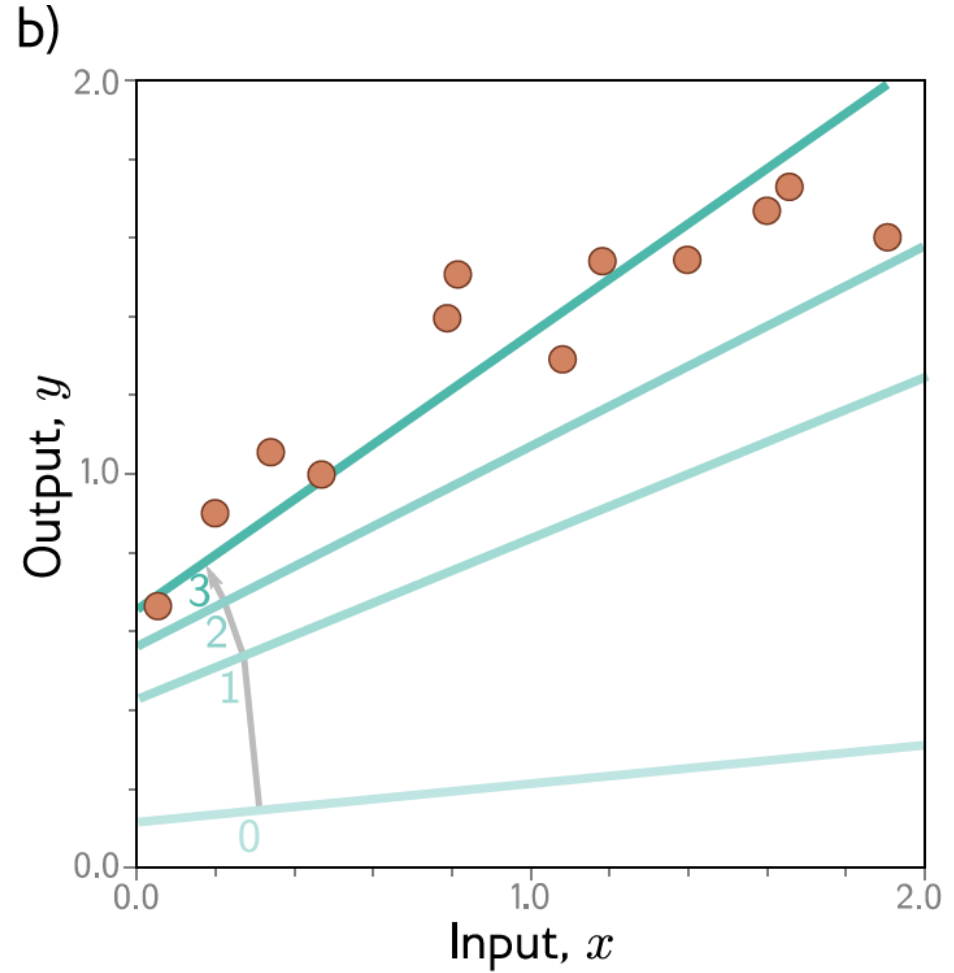
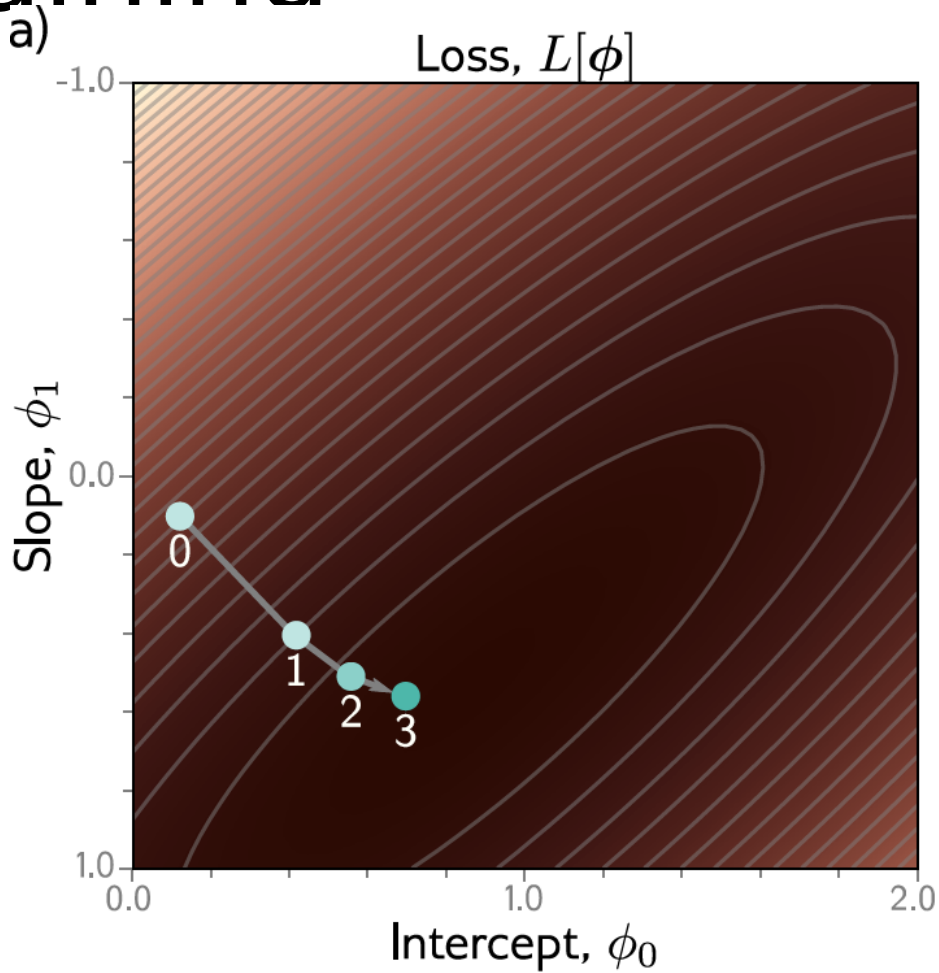
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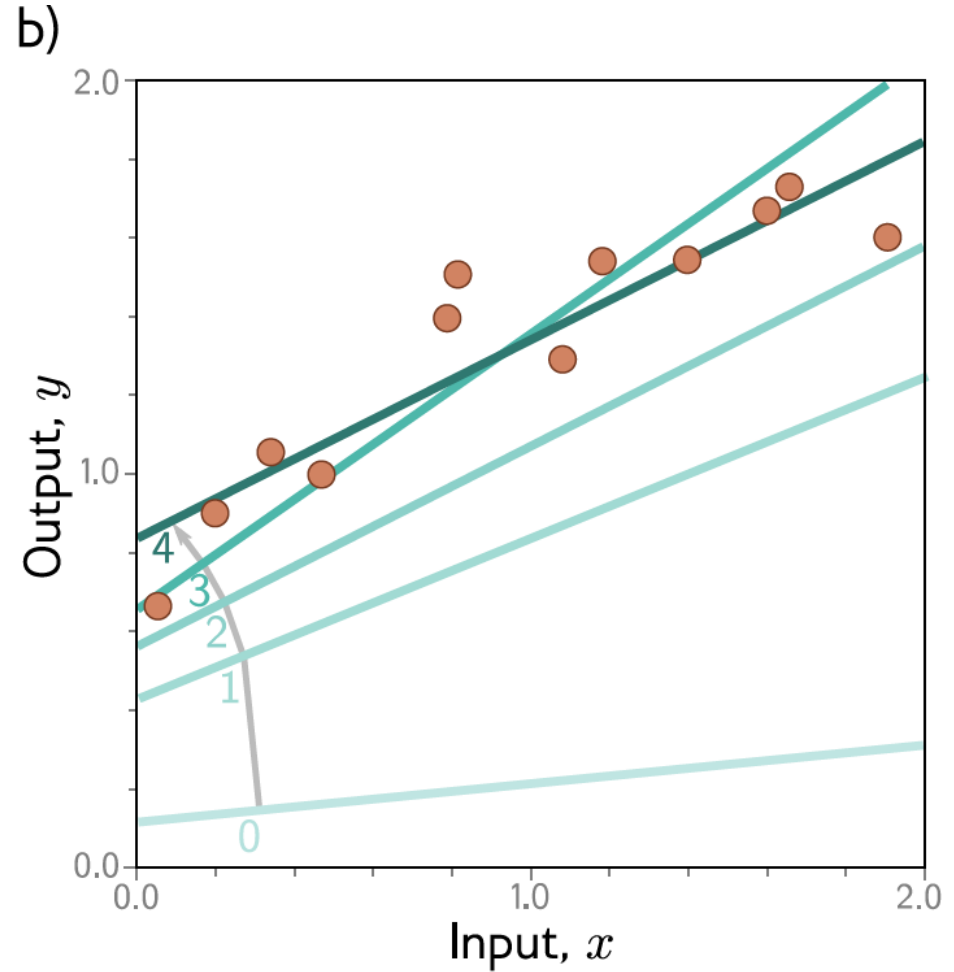
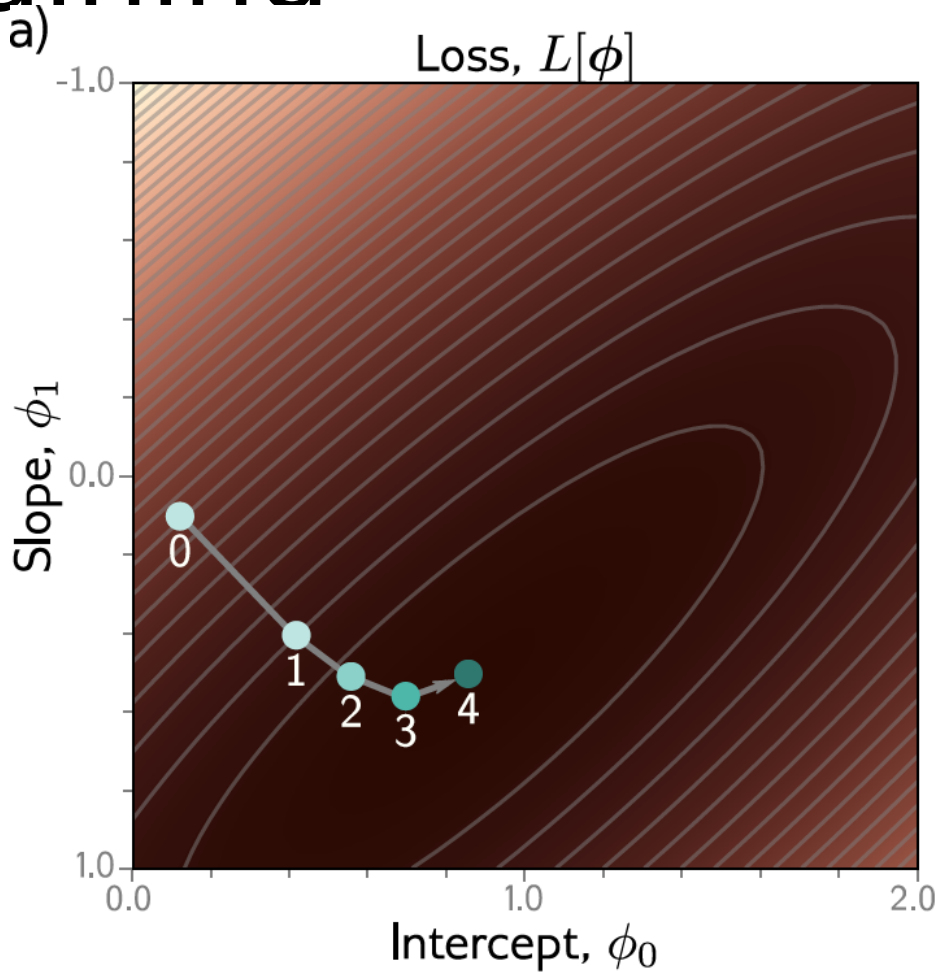
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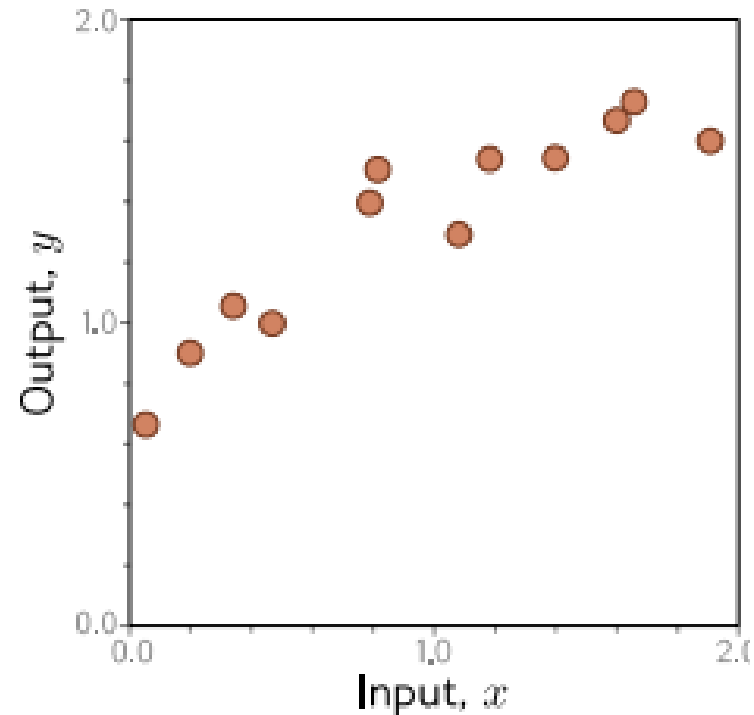
Example: 1D Linear regression training



This technique is known as **gradient descent**

Example: 1D Linear regression testing

- Test with different set of paired input/output data
 - Measure performance
 - Degree to which this is same as training = **generalization**
- Might not generalize well because
 - Model too simple
 - Model too complex
 - fits to statistical peculiarities of data
 - this is known as **overfitting**



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Where are we going?

- Shallow neural networks (a more flexible model)
- Deep neural networks (an even more flexible model)
- Loss functions (where did least squares come from?)
- How to train neural networks (gradient descent and variants)
- How to measure performance of neural networks (generalization)