



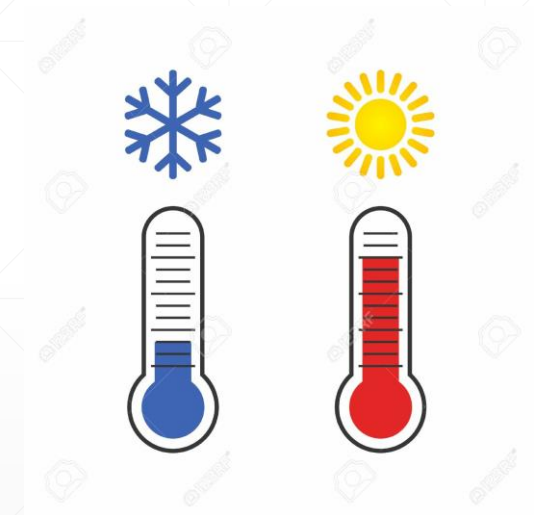
# 回归问题

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主讲人：龙良曲

# Machine Learning

- make decisions
- going left/right → discrete
- increase/decrease → continuous



# Continuous Prediction

- $f_{\theta}: x \rightarrow y$
- $x$ : input data
- $f(x)$ : prediction
- $y$ : real data, ground-truth



# Linear Equation

- $y = w * x + b$
- $1.567 = w * 1 + b$
- $3.043 = w * 2 + b$
- $w = 1.477$
- $b = 0.089$



# With Noise?

- $y = w * x + b + \epsilon$
- $\epsilon \sim N(0, 1)$

- $1.567 = w * 1 + b + \text{eps}$
- $3.043 = w * 2 + b + \text{eps}$
- $4.519 = w * 3 + b + \text{eps}$
- ...

$$Y = (WX + b)$$

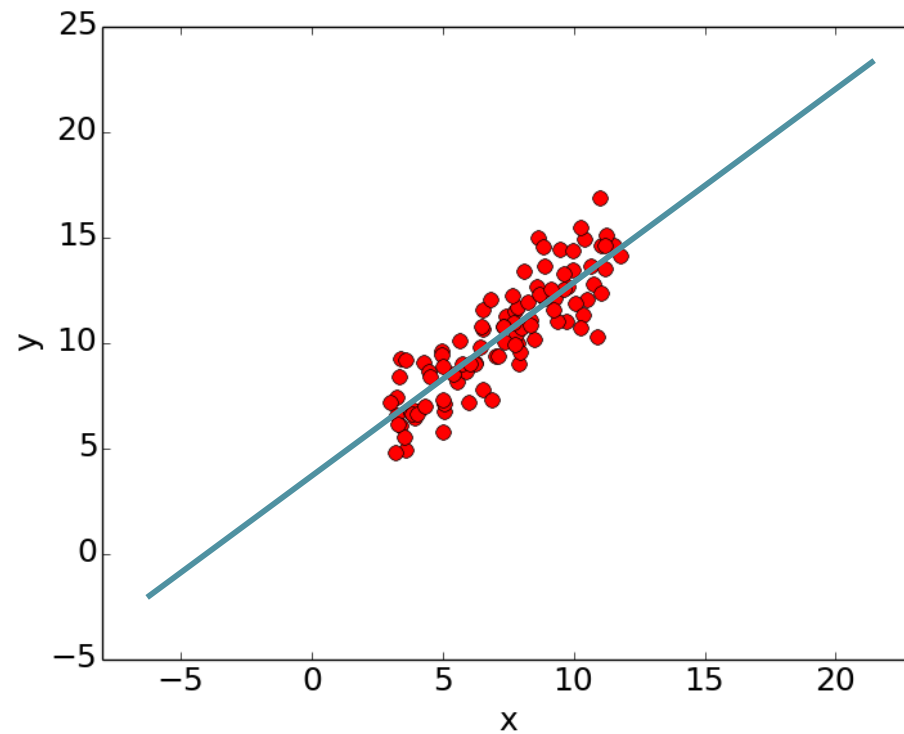


# For Example

- $y = 1.477 * x + 0.089 + \epsilon$

- $w?$

- $b?$



# Find $w', b'$

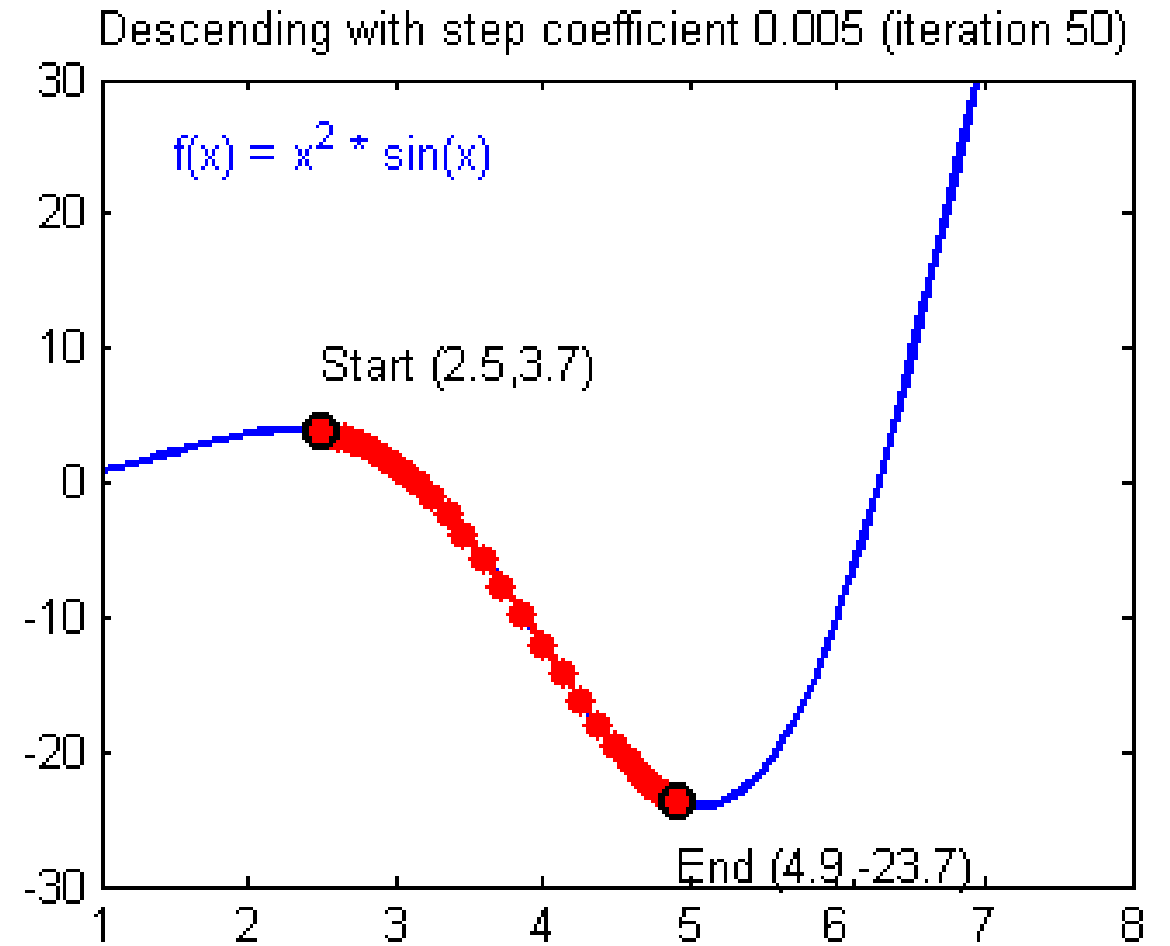
- $(WX + b - Y)^2$
- $loss = \sum_i (w * x_i + b - y_i)^2$
- Minimize  $loss$
- $w' * x + b' \rightarrow y$



# Gradient Descent

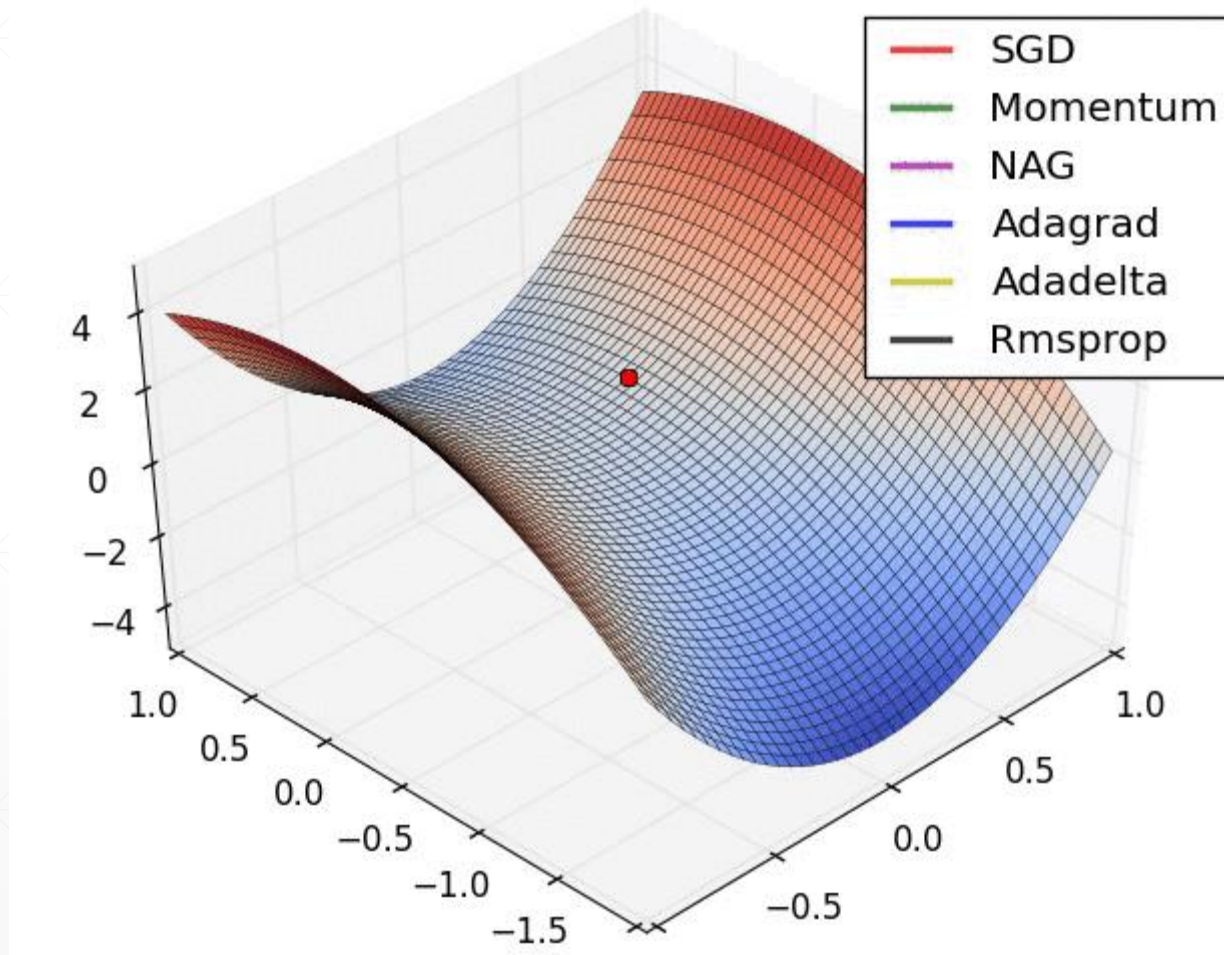
$$w' = w - lr * \frac{dy}{dw}$$

$$x' = x - 0.005 * \frac{dy}{dx}$$





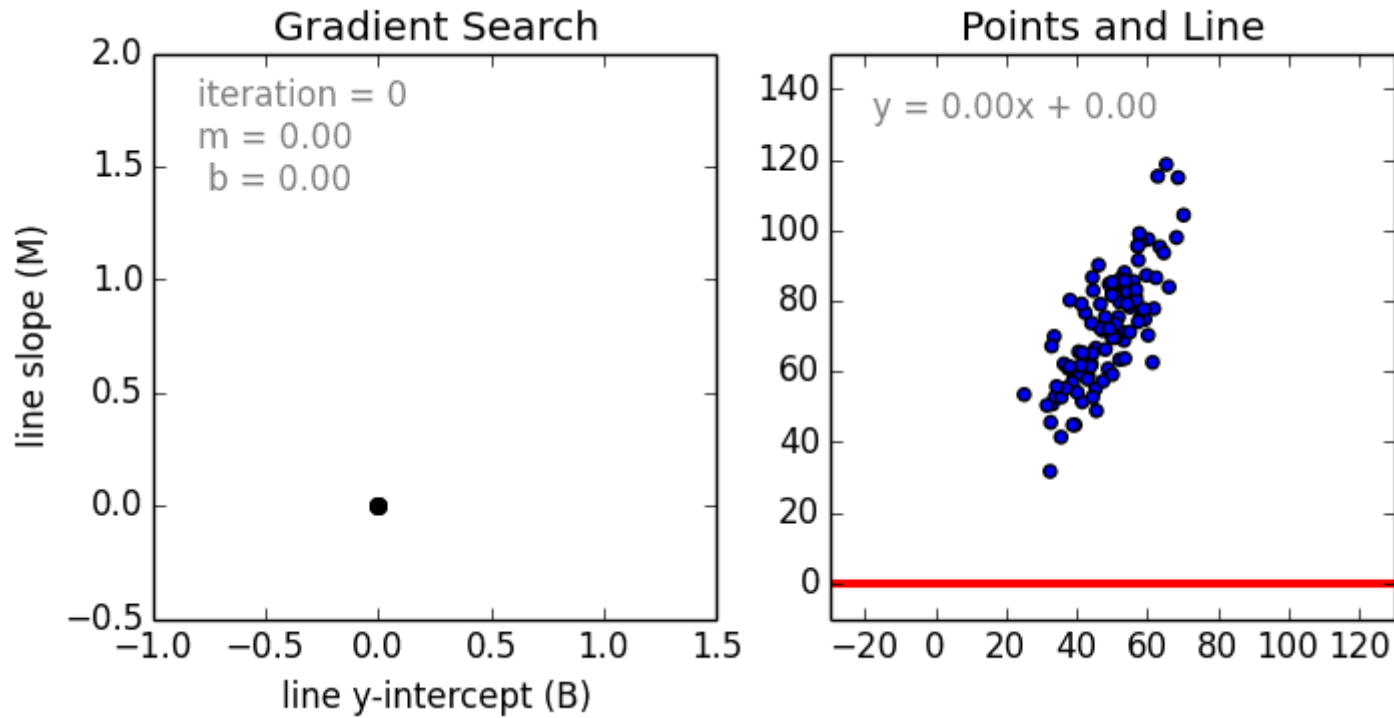
# Gradient Descent



# Find $w', b'$

- $loss = \sum_i (w * x_i + b - y_i)^2$
  - $w' = w - lr * \frac{\partial loss}{\partial w}$
  - $b' = b - lr * \frac{\partial loss}{\partial b}$
  - $w' * x + b' \rightarrow y$
-

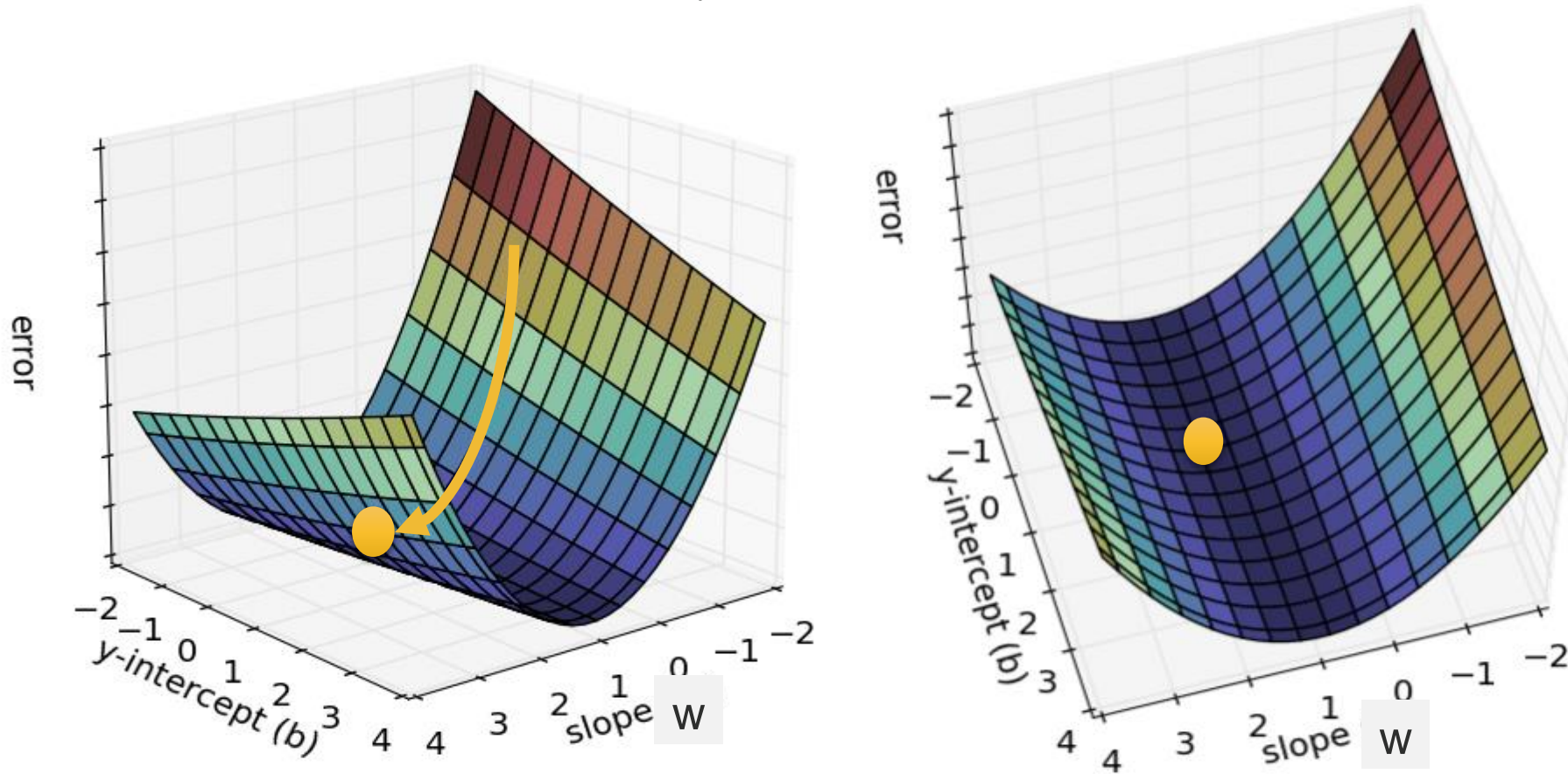
# Learning Process



# Loss surface

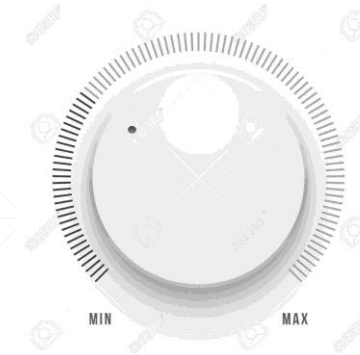
$$\text{loss} = \sum_{i=1} (w * x_i + b - y_i)^2$$

Convex  
Optimization



# Linear Regression

- Linear Regression
- Logistic Regression
- Classification



# 下一课时

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实战Linear  
Regression



**Thank You.**

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