



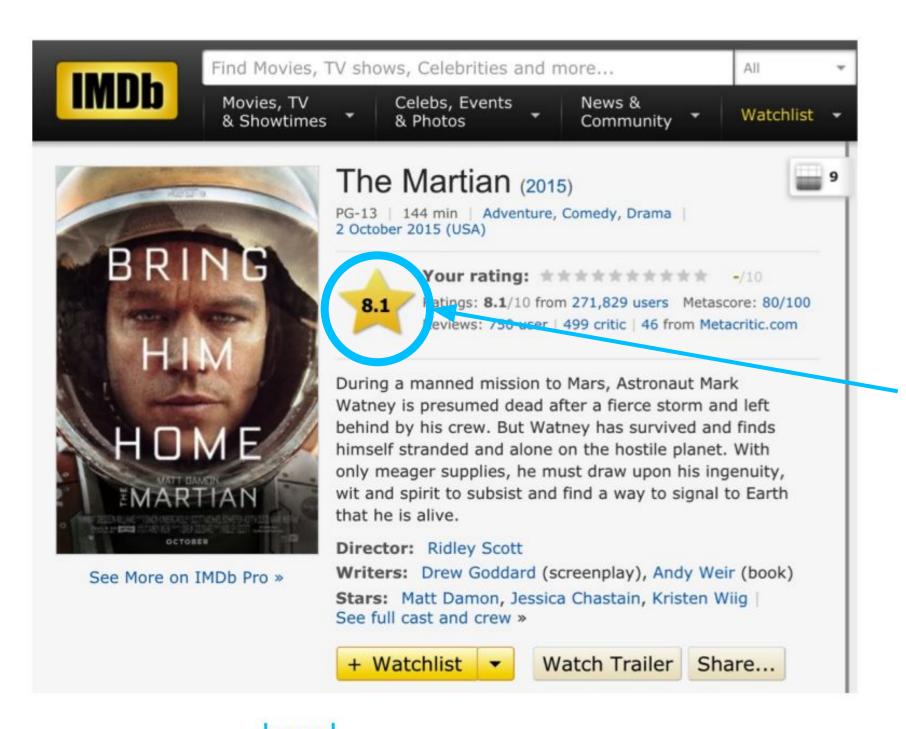
LINEAR REGRESSION

Ariana Villegas





What should I watch?

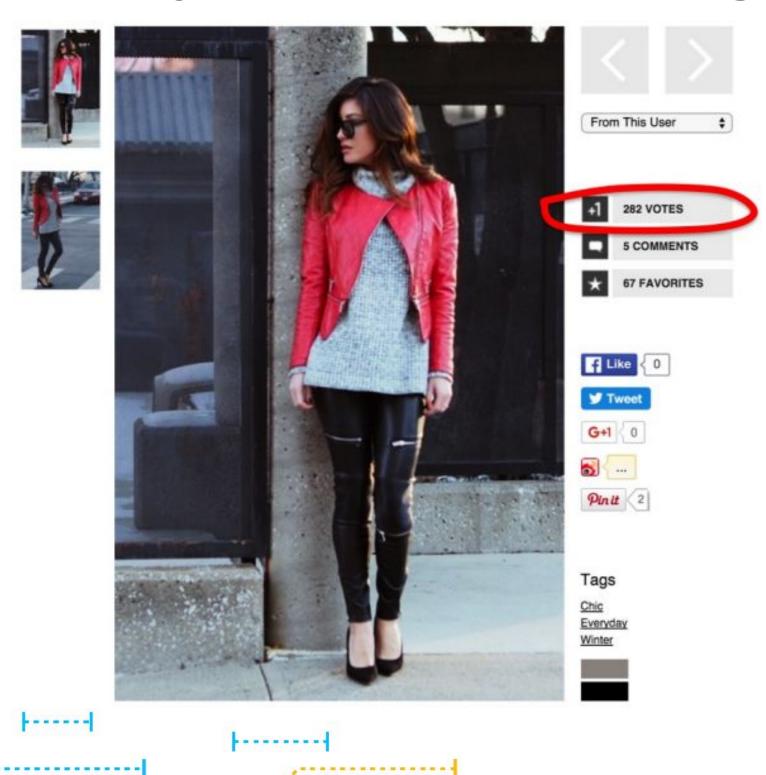


Can we predict this?



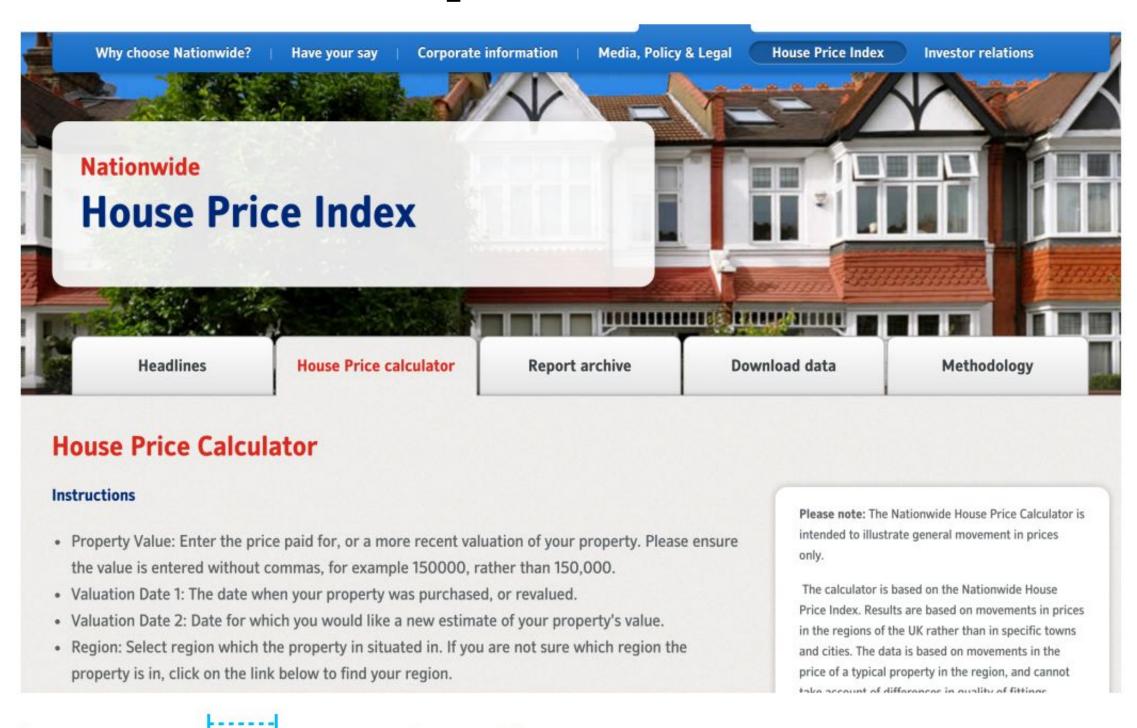


How many followers will I get?





Predict the price of the house











What do all these problems have in common?











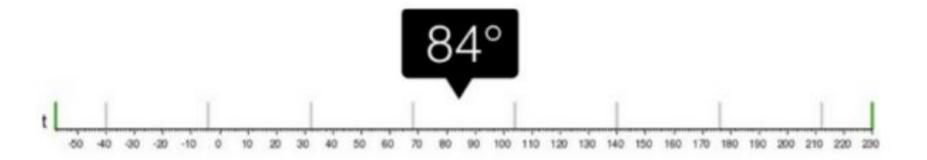


Classification: given point x, predict class (often binary)

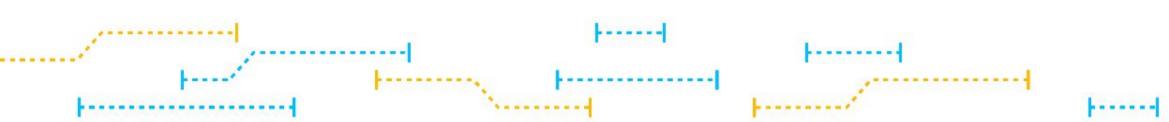
Regression: given point x, predict a numerical value



What will be the temperature tomorrow?



Fahrenheit

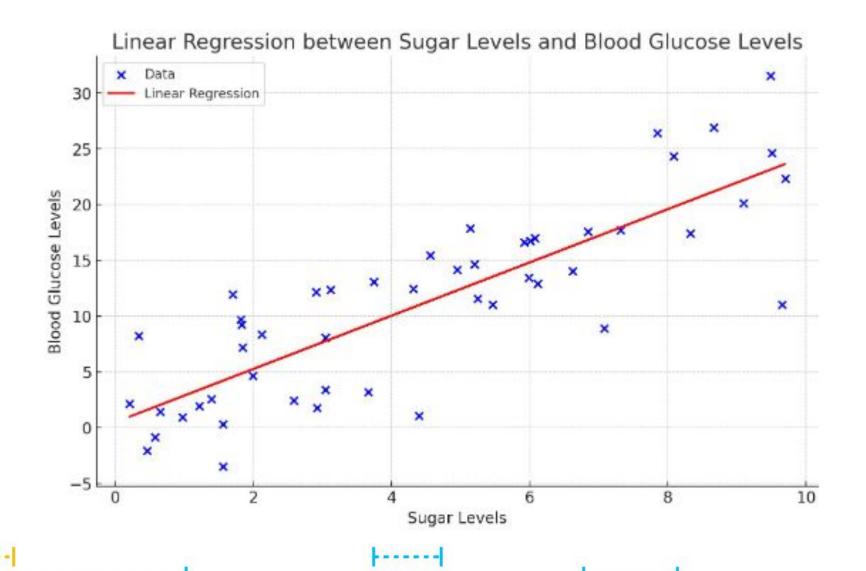






Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?



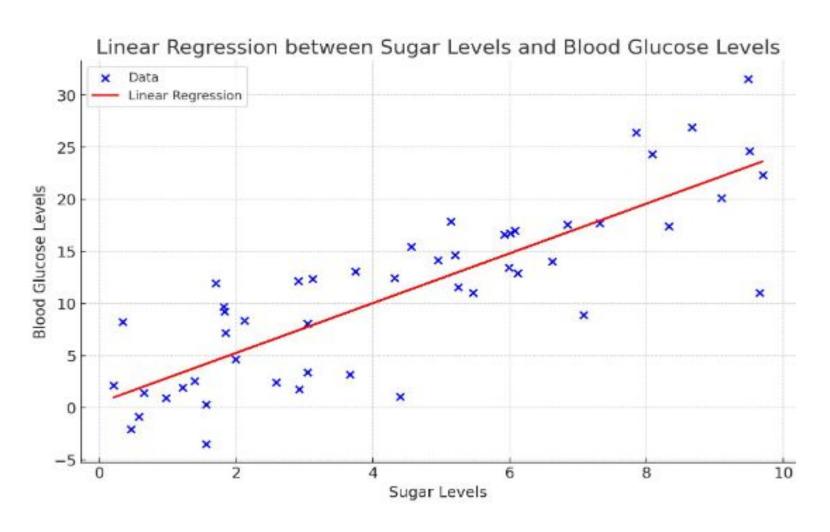
Sugar Levels	Blood Glucose Levels
3.75	13.06
9.51	24.62
7.32	17.72
5.99	13.46
1.56	-3.49





Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?



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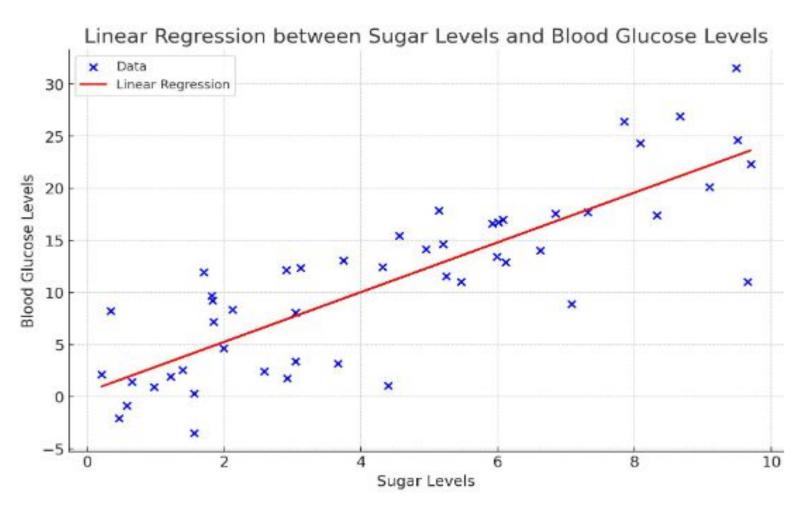
$$f(x) = mx + b$$





Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?



Input	(x)	Output	(y)
-------	-----	--------	------------

Sugar Levels	Blood Glucose Levels	
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$$f(x) = mx + b$$

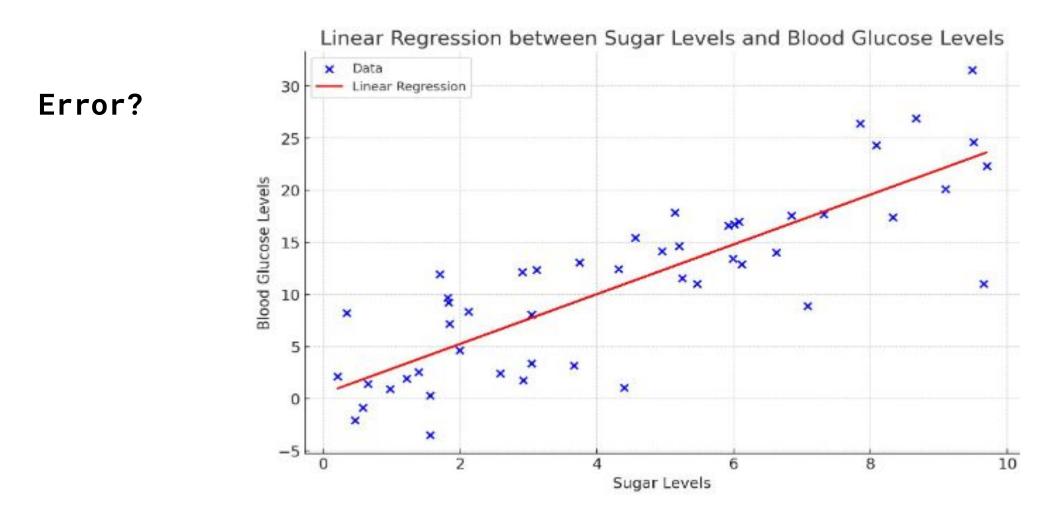
Model





Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?



Output (y)
Blood Glucose Levels
13.06
24.62
17.72
13.46
-3.49

$$f(x) = mx + b$$
Model





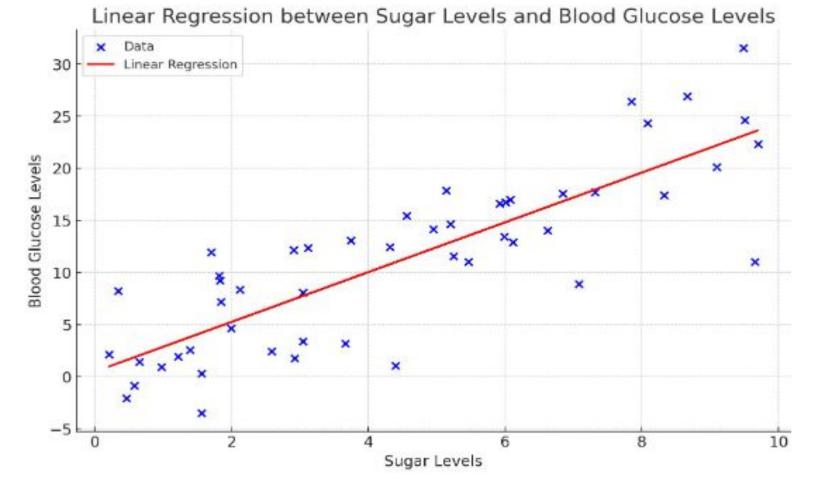
Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?



MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2$$

$$MAE = rac{1}{N} \sum_{i=1}^N \lvert y_i - \hat{y}_i
vert$$



Input	(x)	Output	(y)
-------	-----	--------	------------

Sugar Levels	Blood Glucose Levels
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$$f(x) = mx + b$$

Model





What do I need in order to predict these outputs?

Least Squares Regression: y = mx + b

$$\mathbf{m} = \frac{N \Sigma(xy) - \Sigma x \Sigma y}{N \Sigma(x^2) - (\Sigma x)^2} \qquad \mathbf{b} = \frac{\Sigma y - m \Sigma x}{N}$$

$$\mathbf{b} = \frac{\Sigma y - m \; \Sigma x}{N}$$

$$y = mx + b$$



Loss Function vs Metrics

Simply put, loss function is for machines, and metric is for humans.

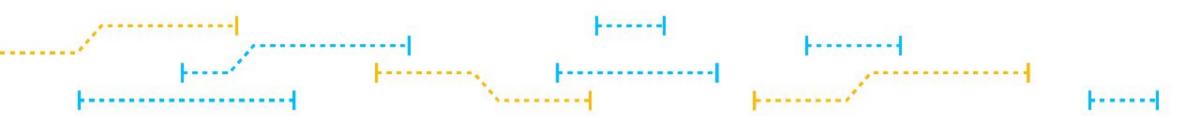
Loss function is what the machine tries to minimize in order to optimize the machine learning model.

Metrics are utilized by people to evaluate the performance of machine learning models and has nothing to do with the optimization process.

Can they be used interchangeably?

A loss function can be used as a metric, but the opposite isn't always true.

This is due to an important characteristic of loss functions: they must be differentiable.







Condition of a Metric

Definition 7.1. A metric d on a set X is a function $d: X \times X \to \mathbb{R}$ such that for all $x, y \in X$:

- (1) $d(x,y) \ge 0$ and d(x,y) = 0 if and only if x = y;
- (2) d(x,y) = d(y,x) (symmetry);
- (3) $d(x,y) \le d(x,z) + d(z,x)$ (triangle inequality).

A metric space (X, d) is a set X with a metric d defined on X.

Metric spaces by UCDavis



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Metric spaces by UCDavis



Metrics for Regression

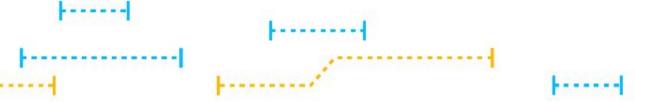
$$MAPE = \frac{\sum \frac{|A - F|}{A} \times 100}{N}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_j)}$$

R2 Squared =
$$1 - \frac{SSr}{SSm}$$

SSr = Squared sum error of regression line

SSm = Squared sum error of mean line





2.







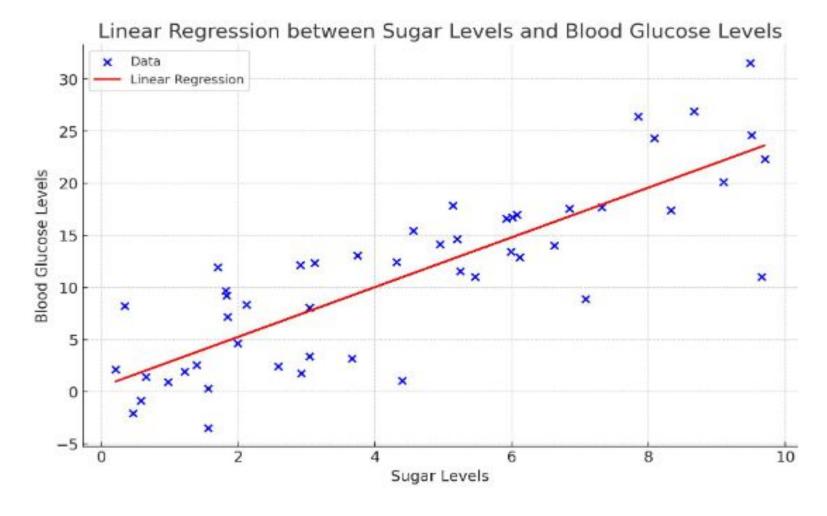
Regression: given point x, predict a numerical value

What do I need in order to predict these outputs?

Error

MSE?

MAE?



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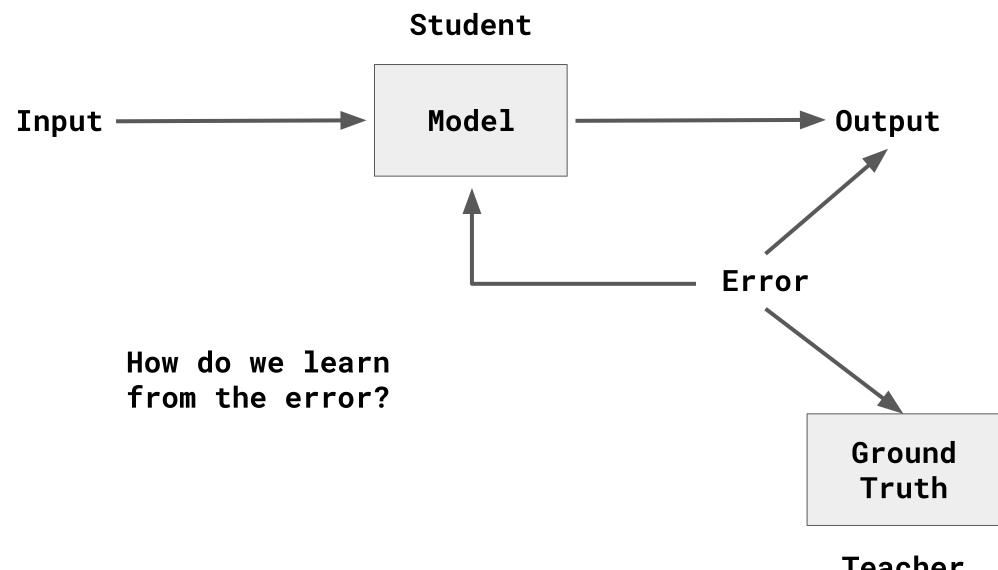
$$f(x) = ax + b \Rightarrow f(x) = wx + b$$

Model

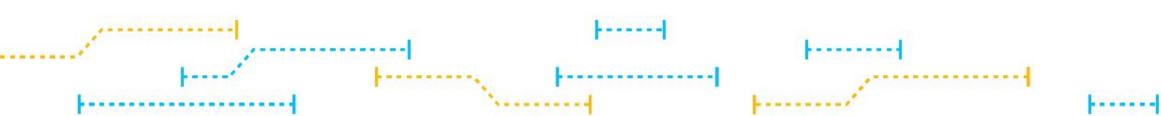




Regression



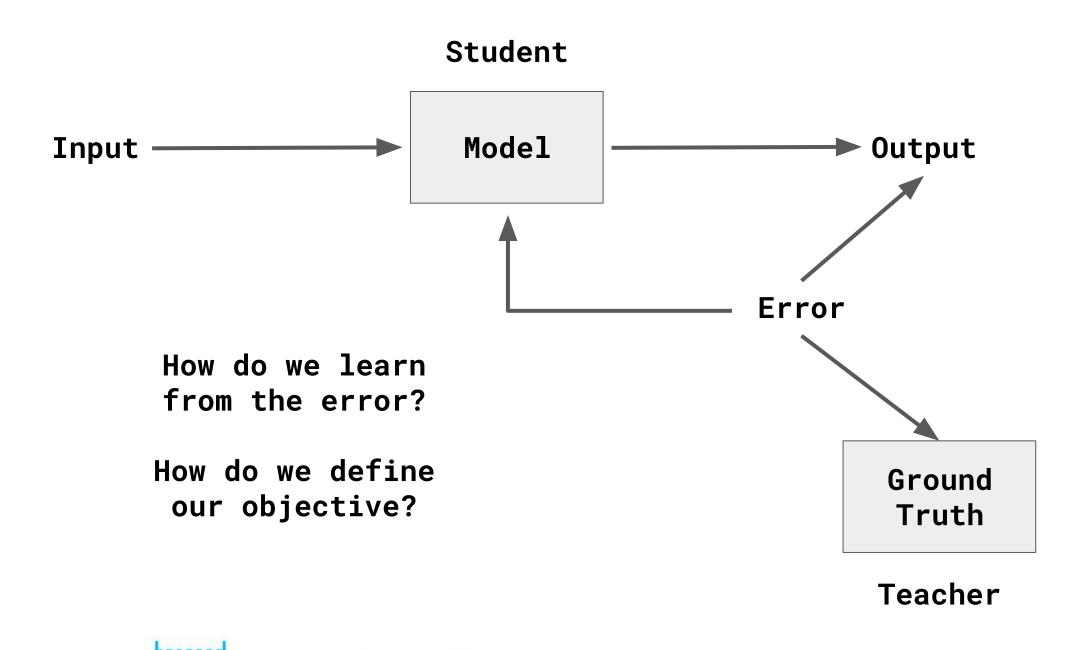
Teacher





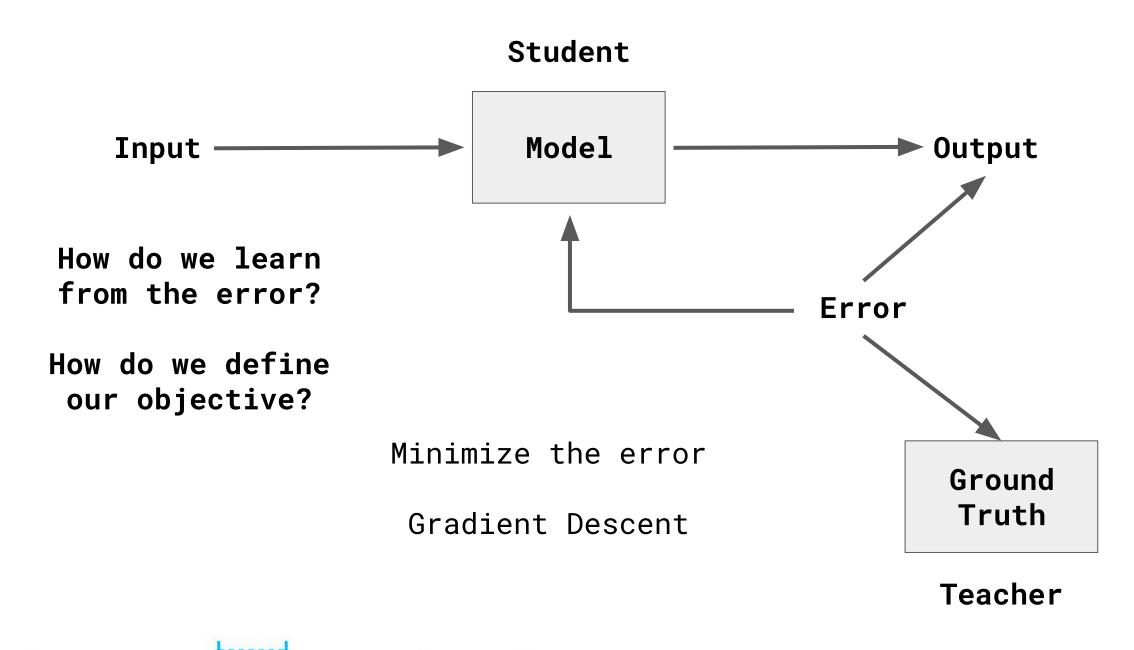


Regression





Regression

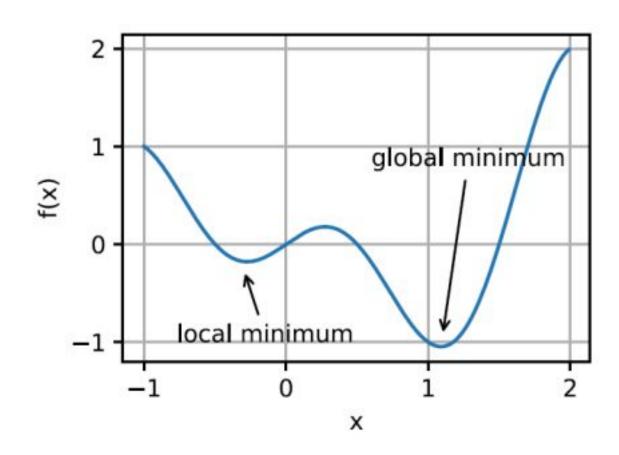


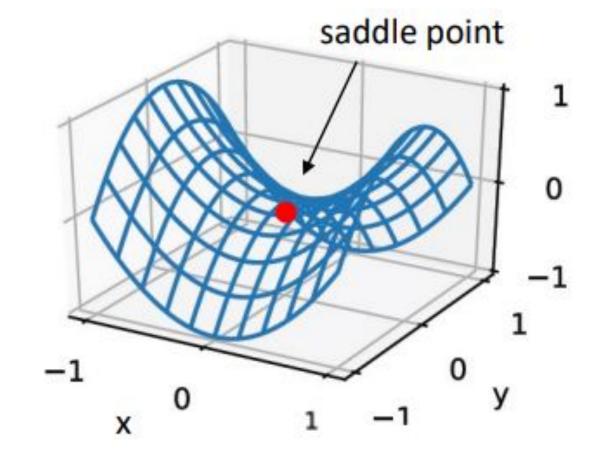


Gradient Descent - Optimization

$$\nabla_{\mathbf{x}} f(\mathbf{x}) = \left[\frac{\partial f(\mathbf{x})}{\partial x_1}, \frac{\partial f(\mathbf{x})}{\partial x_2}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_n} \right]^T$$

$$\nabla_{\mathbf{x}} f(\mathbf{x}) = \begin{bmatrix} \frac{\partial f(\mathbf{x})}{\partial x_1}, \frac{\partial f(\mathbf{x})}{\partial x_2}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_n} \end{bmatrix}^T \qquad x_1 = x_1 - \alpha \frac{\partial f(x)}{\partial x_1} \quad x_2 = x_2 - \alpha \frac{\partial f(x)}{\partial x_2}$$



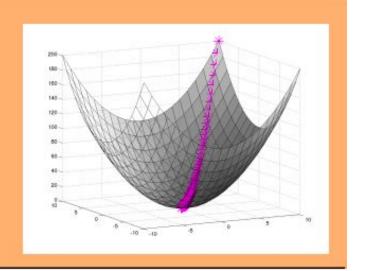




Gradient Descent

Algorithm 1 Gradient Descent

- 1: procedure $GD(\mathcal{D}, \boldsymbol{\theta}^{(0)})$
- 2: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta}^{(0)}$
- 3: **while** not converged **do**
- 4: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} \gamma \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$
- 5: return θ



$$\nabla_{\mathbf{x}} f(\mathbf{x}) = \begin{bmatrix} \frac{\partial f(\mathbf{x})}{\partial x_1}, \frac{\partial f(\mathbf{x})}{\partial x_2}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_n} \end{bmatrix}^T \qquad x_1 = x_1 - \alpha \frac{\partial f(x)}{\partial x_1} \quad x_2 = x_2 - \alpha \frac{\partial f(x)}{\partial x_2}$$



Stochastic Gradient Descent

Algorithm 1 Stochastic Gradient Descent (SGD)

```
1: procedure SGD(\mathcal{D}, \theta^{(0)})
2: \theta \leftarrow \theta^{(0)}
3: while not converged do
4: for i \in \text{shuffle}(\{1, 2, \dots, N\}) do
5: \theta \leftarrow \theta - \gamma \nabla_{\theta} J^{(i)}(\theta)
6: return \theta
```

$$\nabla_{\mathbf{x}} f(\mathbf{x}) = \begin{bmatrix} \frac{\partial f(\mathbf{x})}{\partial x_1}, \frac{\partial f(\mathbf{x})}{\partial x_2}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_n} \end{bmatrix}^T \qquad x_1 = x_1 - \alpha \frac{\partial f(x)}{\partial x_1} \quad x_2 = x_2 - \alpha \frac{\partial f(x)}{\partial x_2}$$





Linear Regression

Model Prediction / Output \longrightarrow f(x) = y' = wx + bGround Truth / Label

Minimize the error (MSE, MAE)

Loss = MSE =
$$1/n \sum (f(x) - y)^2$$

$$w = w - \alpha \frac{\partial Loss}{\partial w}$$

$$b = b - \alpha \frac{\partial Loss}{\partial b}$$







Linear Regression

Minimize the error (MSE, MAE)

Loss = MSE =
$$1/2n \sum (f(x) - y)^2$$

$$w = w - \alpha \frac{\partial Loss}{\partial w} = w - \alpha \frac{1}{n} \sum (f(x) - y)x$$

$$b = b - \alpha \frac{\partial Loss}{\partial b} = b - \alpha \frac{1}{n} \sum (f(x) - y)$$

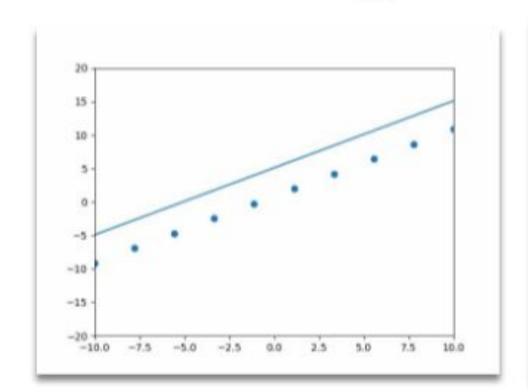


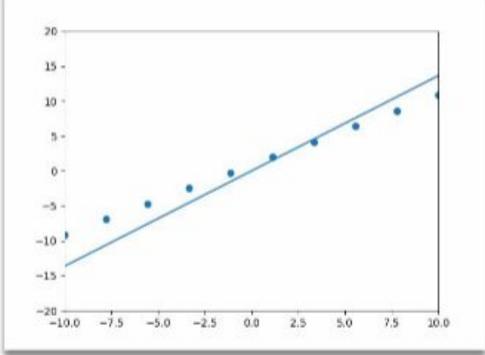
Linear Regression

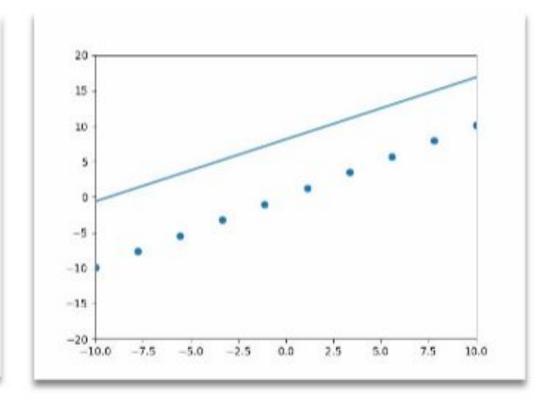
$$L = xw + b$$

$$L = xw + b$$

$$L = xw + b$$









Multidimensional Linear Regression

Imagine now we want to predict the median house price from these multi-dimensional observations

Each house is a data point \mathbf{n} , with observations indexed by \mathbf{j} :

$$\mathbf{x}^{(n)} = \left(x_1^{(n)}, \cdots, x_j^{(n)}, \cdots, x_d^{(n)}\right)$$

We can incorporate the bias \mathbf{w}_{θ} into \mathbf{w} , by using \mathbf{x}_{θ} = 1, then

$$y(\mathbf{x}) = w_0 + \sum_{j=1}^d w_j x_j = \mathbf{w}^T \mathbf{x}$$

We can then solve for $w = (w_0, w_1, \dots, w_d)$. How?



Multidimensional Linear Regression

Imagine now we want to predict the median house price from these **multi-dimensional** observations

Each house is a data point \mathbf{n} , with observations indexed by \mathbf{j} :

$$\mathbf{x}^{(n)} = \left(x_1^{(n)}, \cdots, x_j^{(n)}, \cdots, x_d^{(n)}\right)$$

We can incorporate the bias \mathbf{w}_{a} into \mathbf{w} , by using $\mathbf{x}_{a} = \mathbf{1}$, then

$$y(\mathbf{x}) = w_0 + \sum_{j=1}^d w_j x_j = \mathbf{w}^T \mathbf{x}$$

We can then solve for $w = (w_0, w_1, \dots, w_d)$. How?

We can use gradient descent to solve for each coefficient, or compute w analytically (how does the solution change?)







Multidimensional Linear Regression

Imagine now we want to predict the median house price from
 these multi-dimensional observations

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$$\mathbf{x}^{(n)} = \left(x_1^{(n)}, \cdots, x_j^{(n)}, \cdots, x_d^{(n)}\right)$$

We can use gradient descent to solve for each coefficient, or compute w analytically (how does the solution change?)

$$\vec{\beta} = (X^T X)^{-1} X^T \vec{y}$$

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} N \sum X_i \\ \sum X_i \sum x_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum y \\ \sum X_i y_i \end{bmatrix}$$





3.









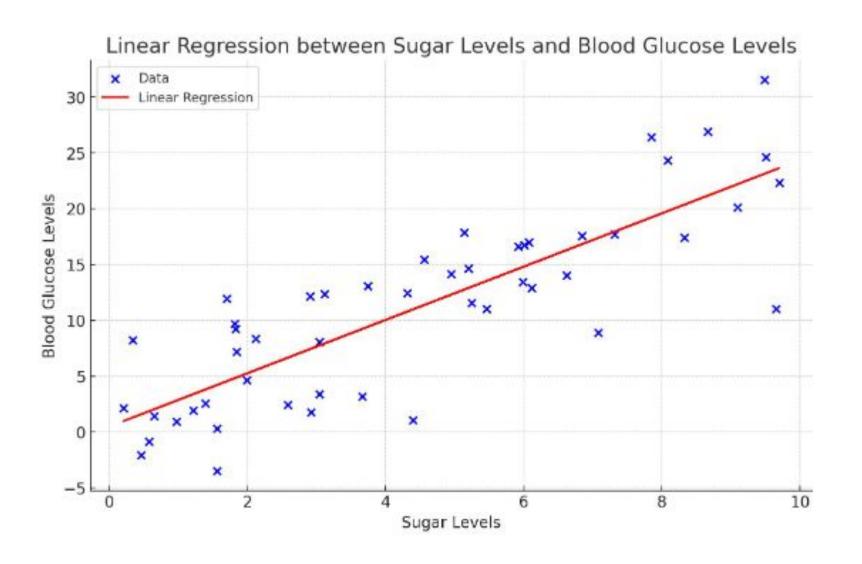


https://www.mladdict.com/line ar-regression-simulator





Home Exercise



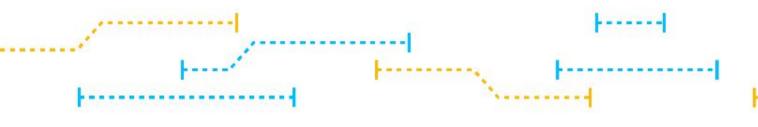
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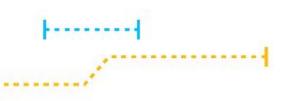
$$f(x) = wx + b$$

$$W = 0$$

$$b = 0$$

$$b = 0$$
 $a = 0.1$











Home Exercise

$$f(x) = wx + b$$
 $w = 0$ $b = 0$ $a = 0.1$

$$W = 0$$

$$b = 0$$

$$a = 0.1$$

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More Exercises?

MACHINE LEARNING WORKOUT: Chapter 5



