Deep Learning

Part 2: Gradient Descent Method

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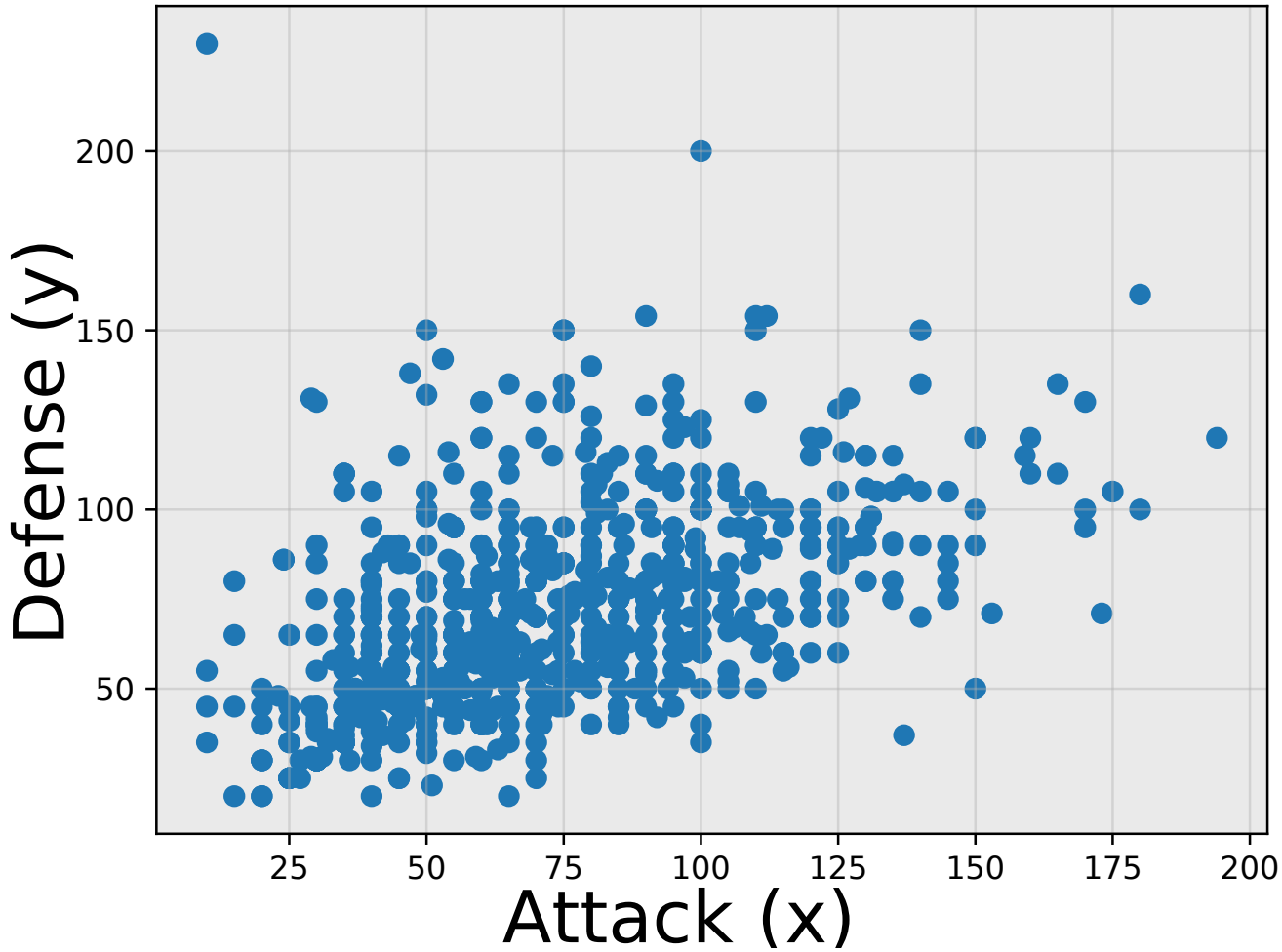
Preliminaries

Preliminaries

1. Define a model (e.g. linear function)
2. Define an objective (e.g. cost function)
3. Minimize the objective function:
   - Try with brute force (too long)
   - Optimal solution (derivative set to zero)
   - Gradient Descent (sign of derivative)

Preliminaries

Pokemon stats: Predict y in function of x



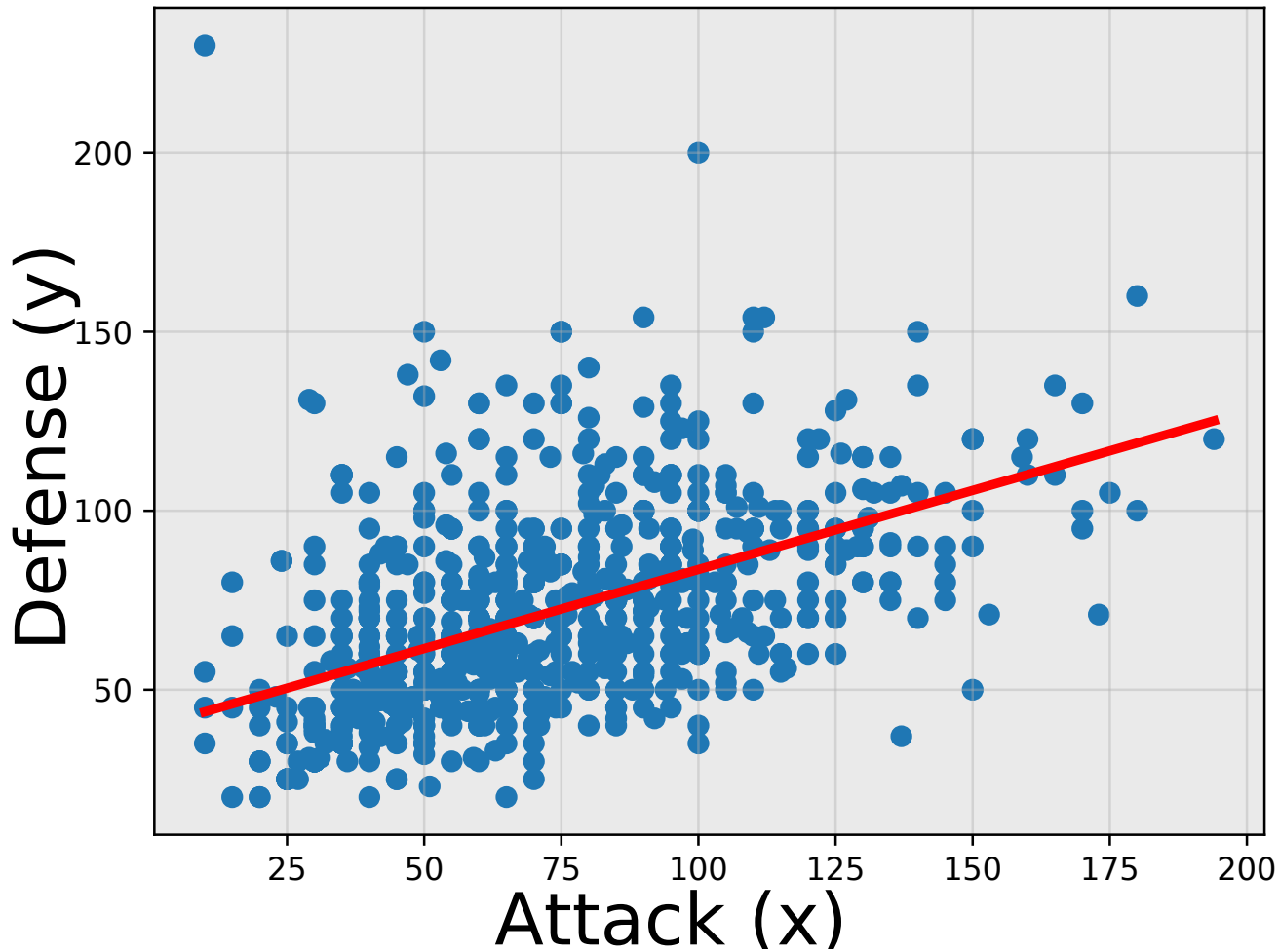
Preliminaries

A hypothesis:

$$\hat{y} = h(x) \tag{1}$$

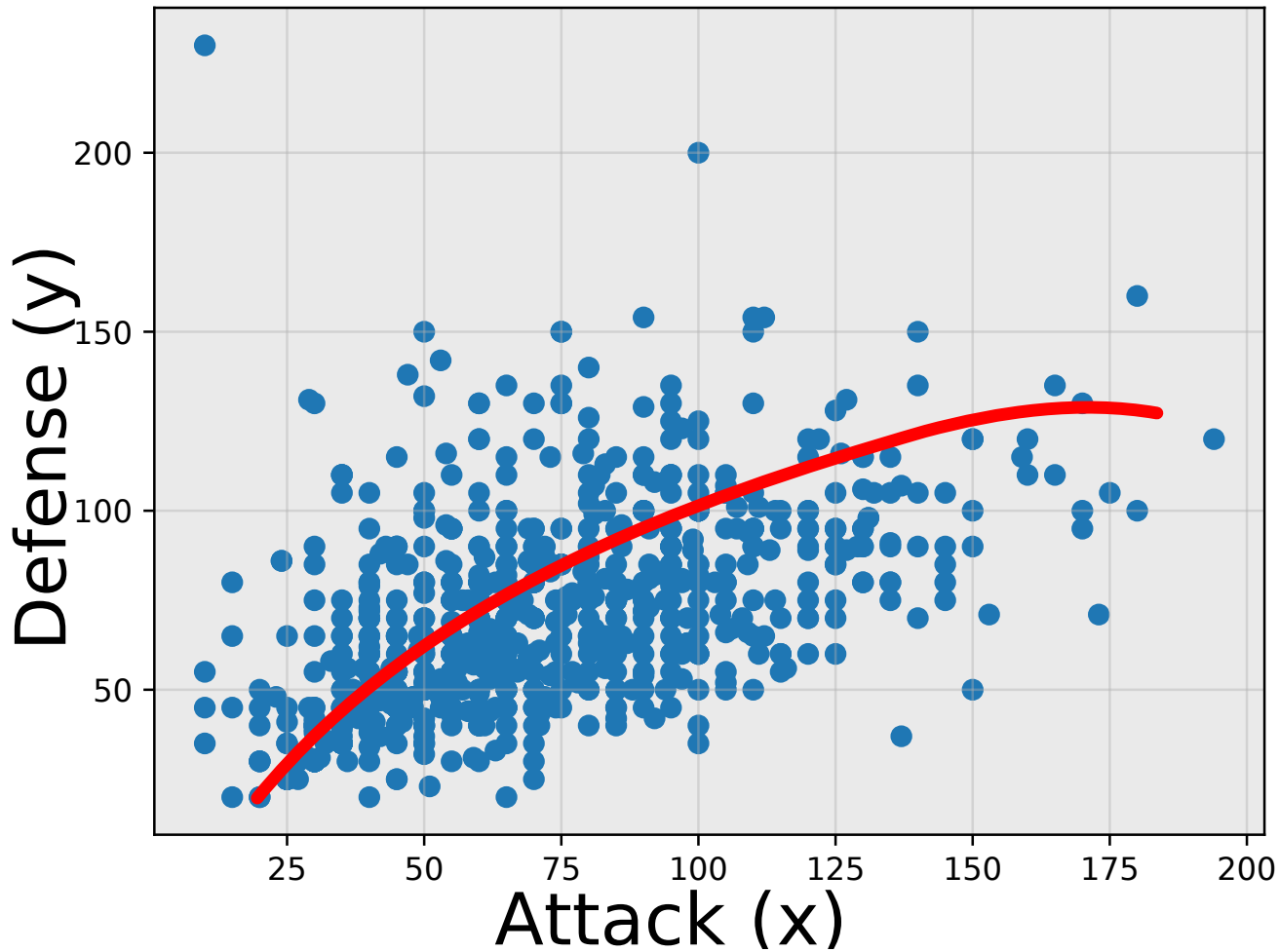
Preliminaries

Hypothesis: straight line $\hat{y} = h(x) = w.x + b$



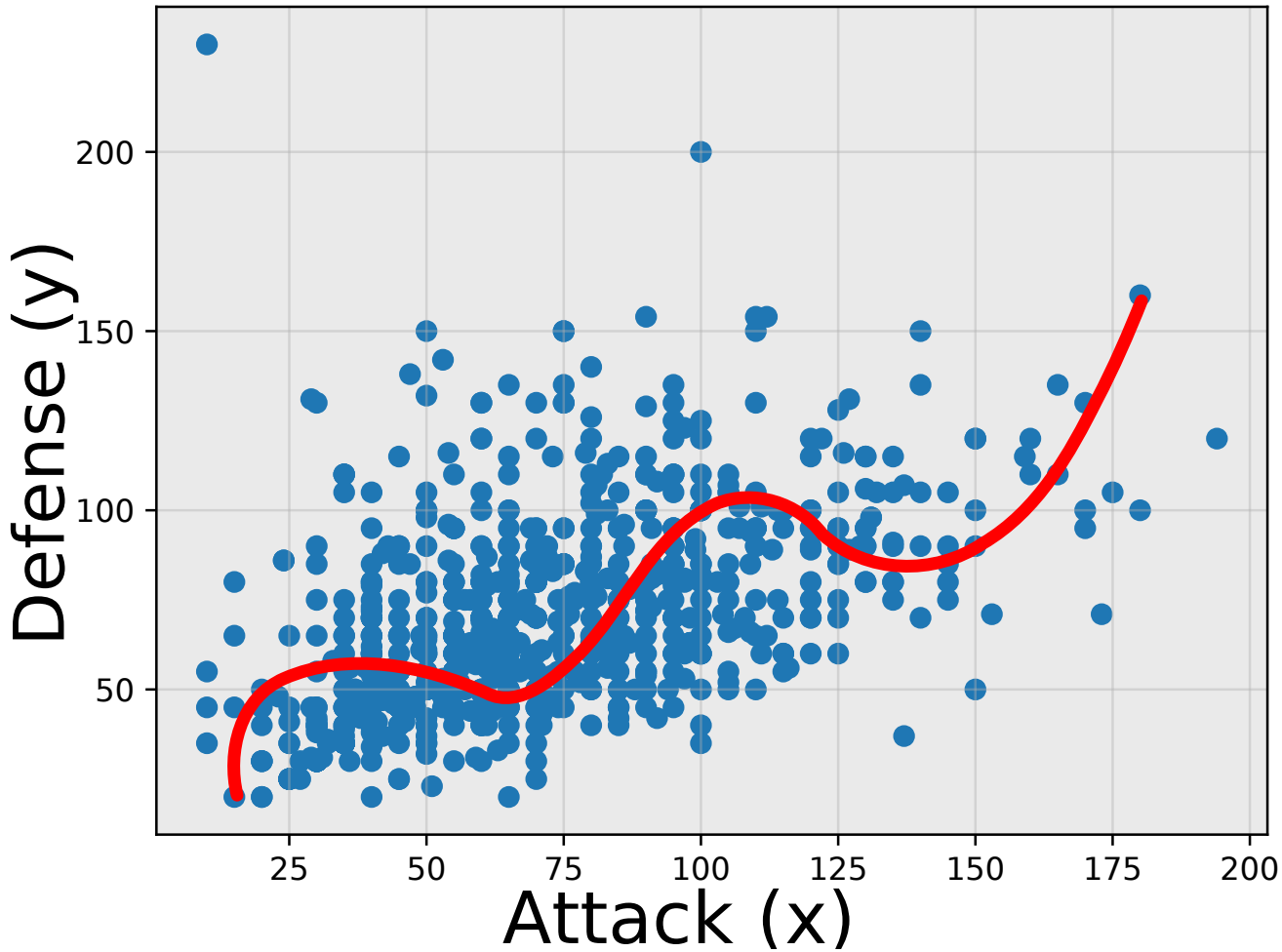
Preliminaries

Hypothesis: curve - 2_{nd} degree parabola $\hat{y} = h(x) = w_1.x^2 + w_2.x + b$



Preliminaries

Hypothesis: complex function $\hat{y} = h(x) = f(x, w_1, w_2, \ldots, w_n)$



Preliminaries

Define the objective

- Cost function:

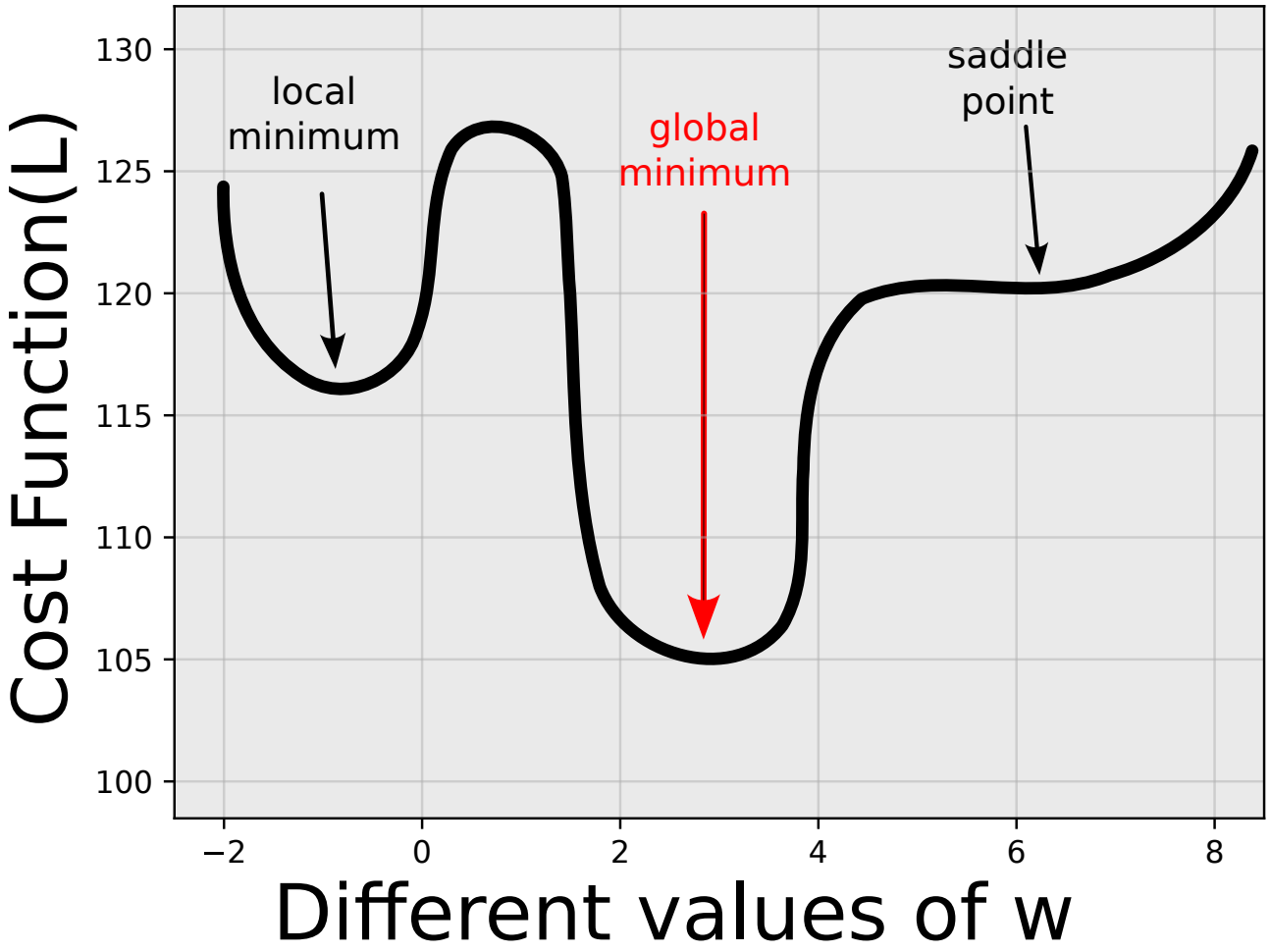
$$L(h) \tag{2}$$

- Objective:

$$\min_{h} L(h) \tag{3}$$

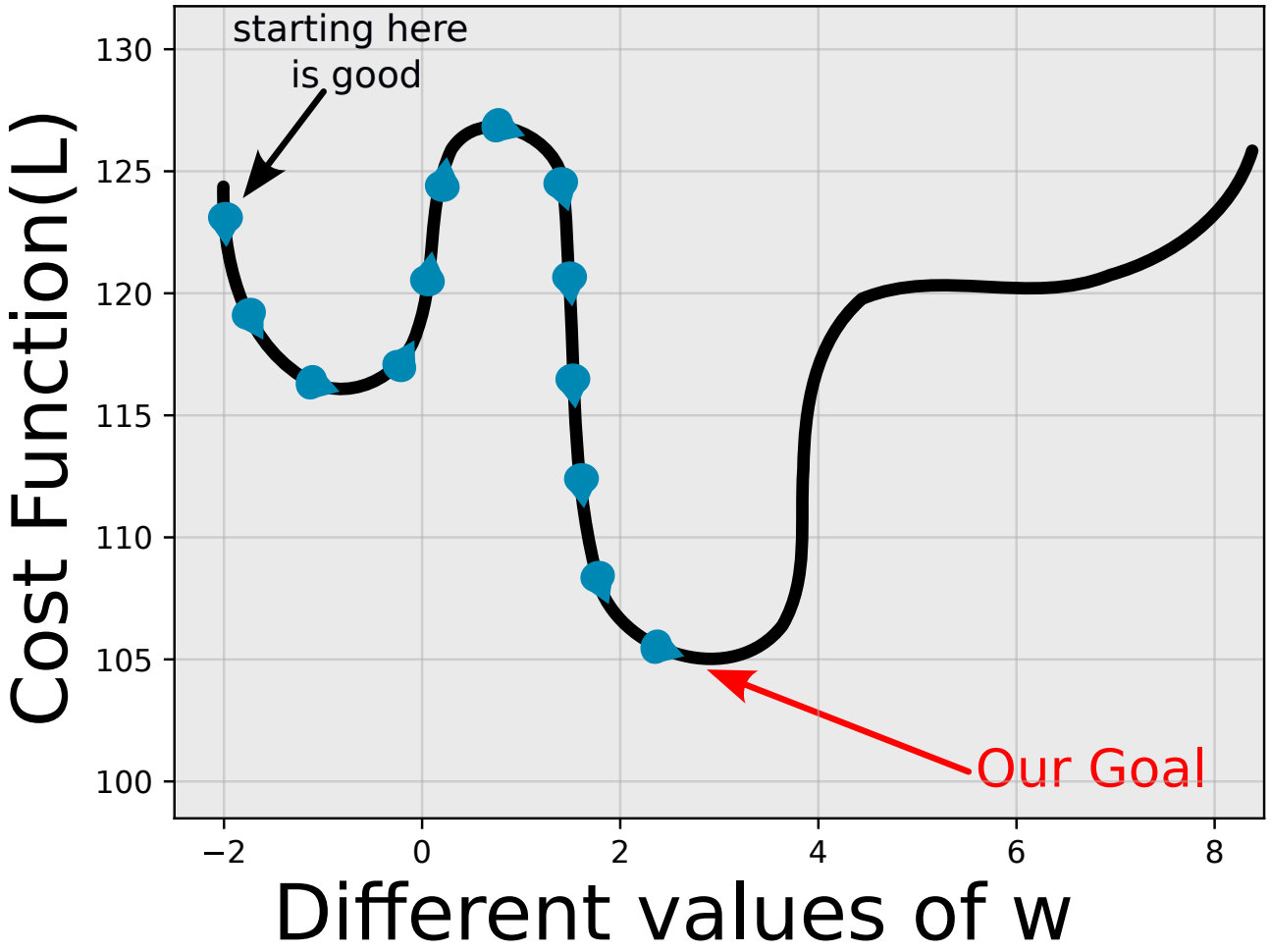
Preliminaries

Minimize a cost function



Preliminaries

Brute Force method



Preliminaries

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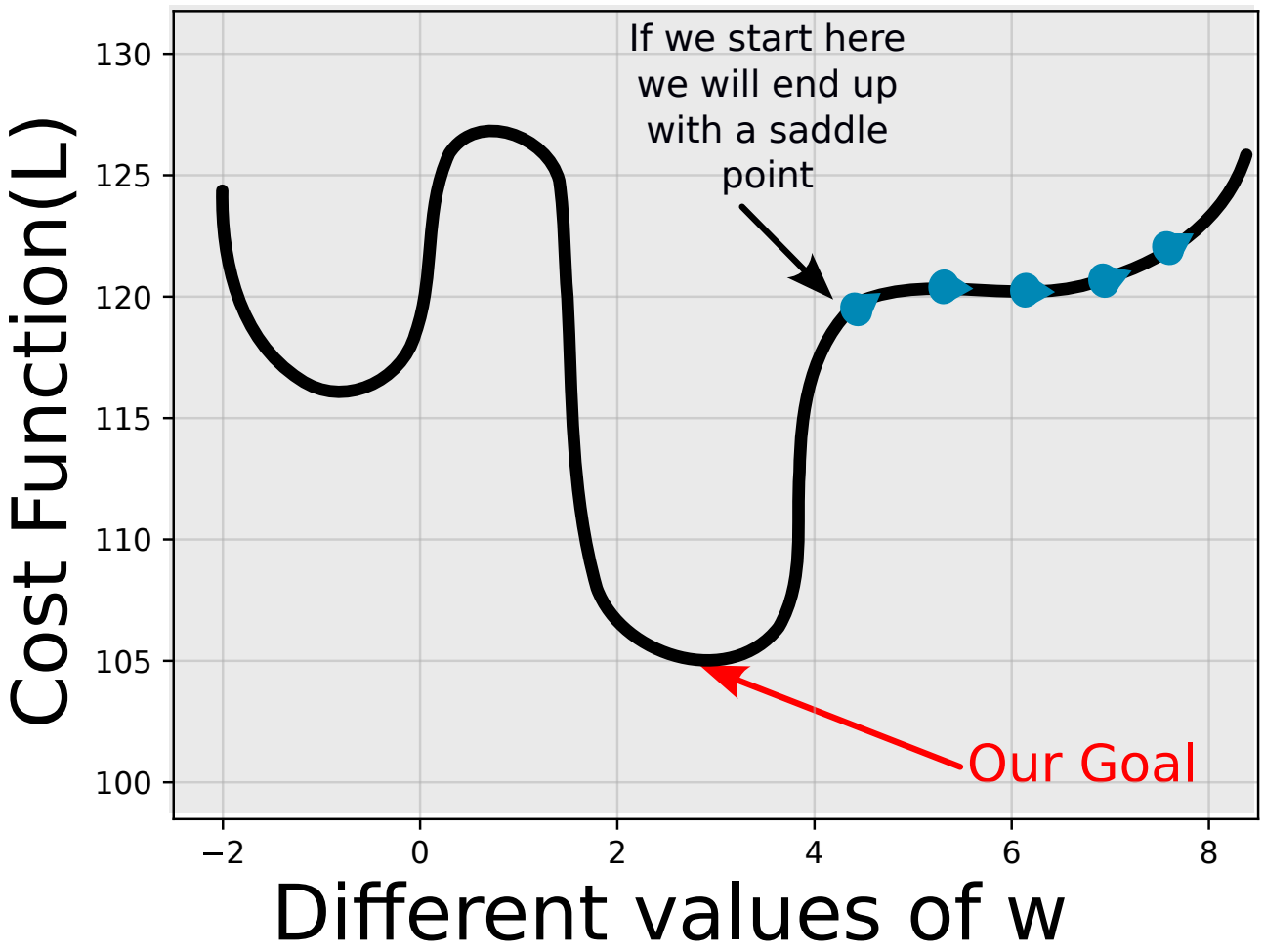


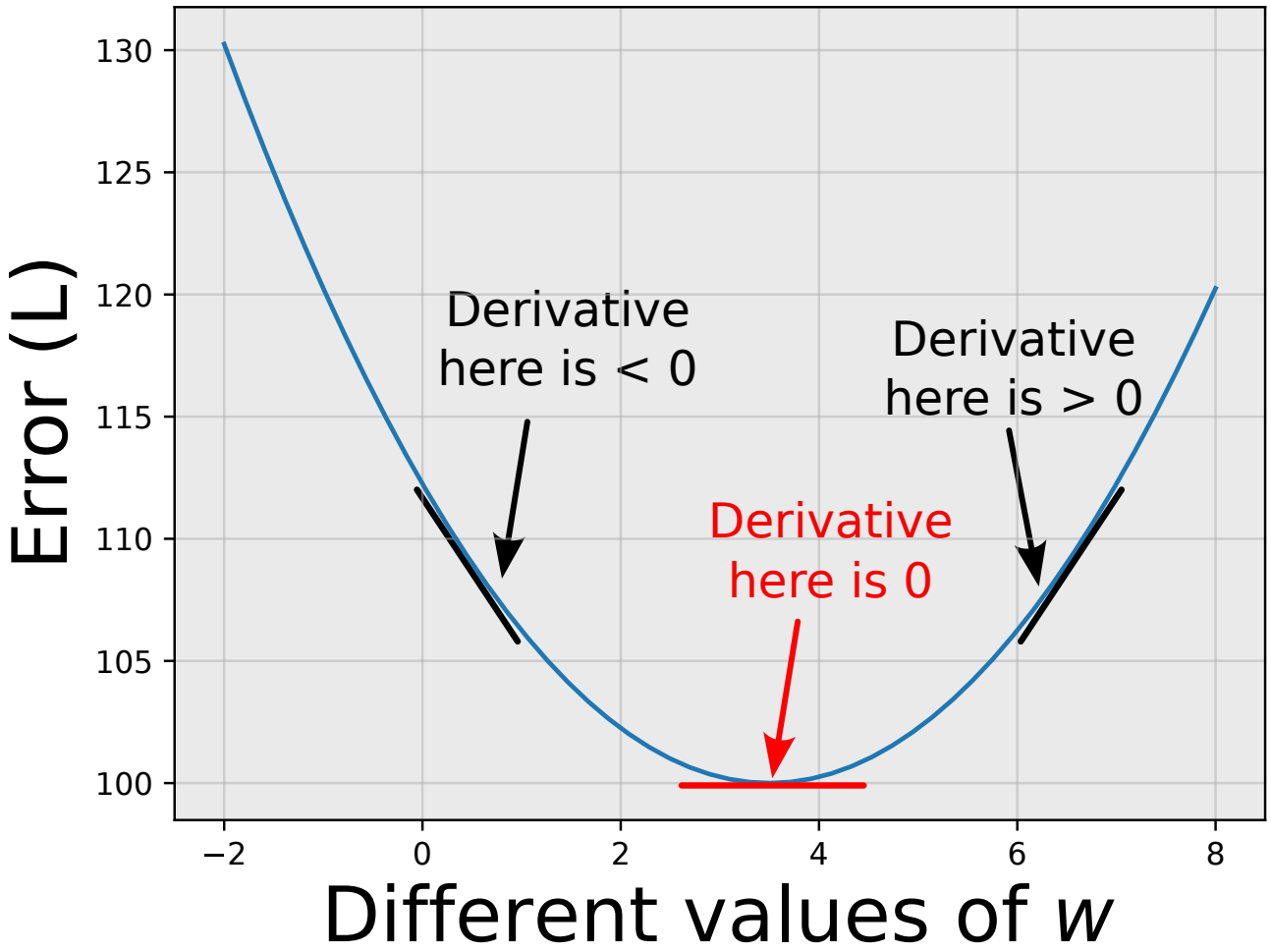
Preliminaries

Brute Force method is not to be used because:

- Very slow methid (if we have $w_1, w_2, \ldots, w_{1000}$
- Difficult to know the starting point
- We can end up with a bad minimum or even a saddle point

Preliminaries

Derivative (Gradient)



Preliminaries

Optimal Solution

- **Goal: Find w such that**

$$\frac{\partial L}{\partial w} = 0 \tag{4}$$

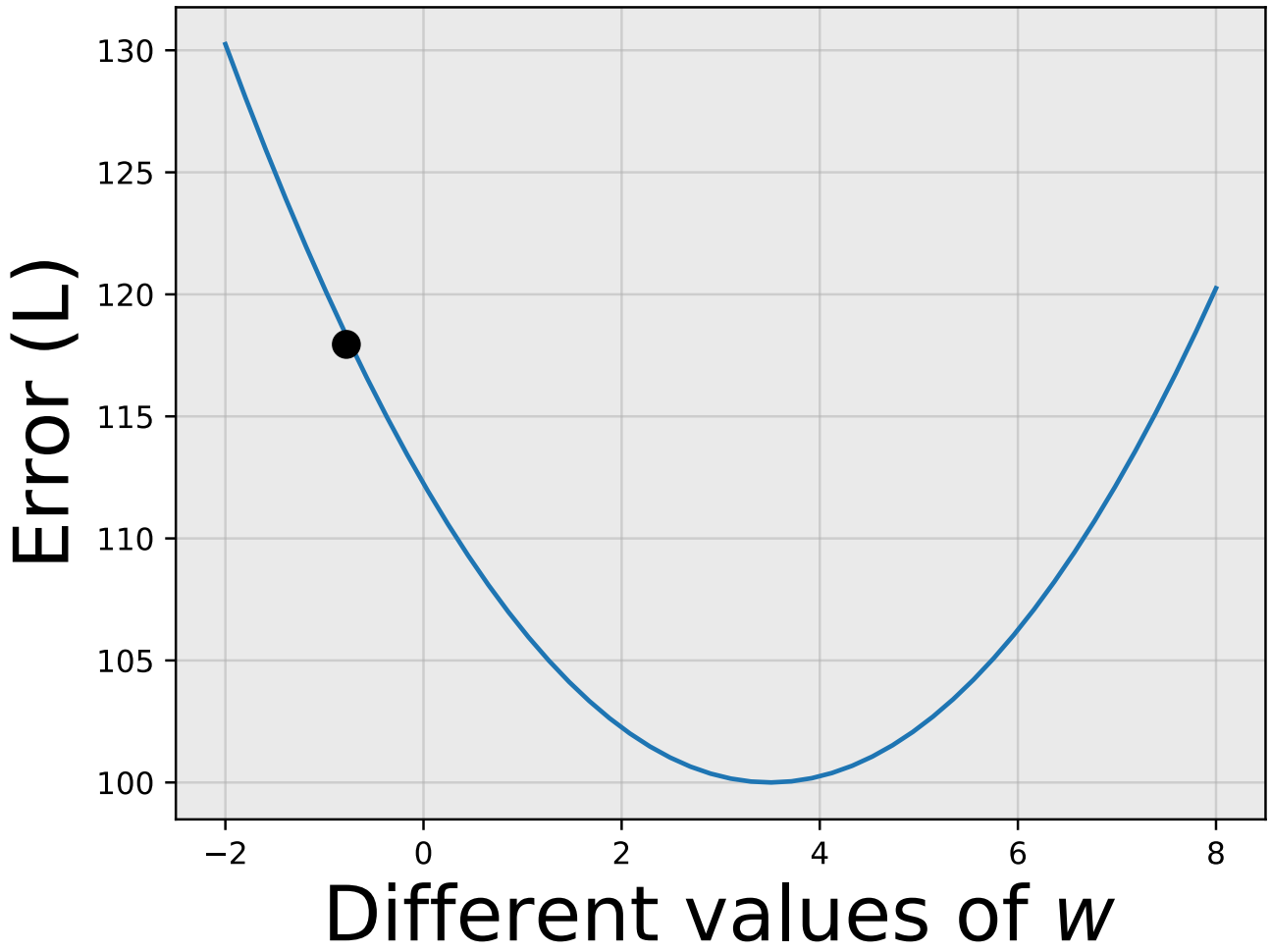
- Many methods exist to solve Equation 4:
  - Inverse normal equations
  - Orthogonal decomposition
- Limitations:
  - Very slow method especially in complex models
  - A problem if many equations exist for Equation 4

Gradient Descent

Gradient Descent

Our friend Ash is blindfolded and wants to arrive to the bottom of the valley to find Mewtwo

Gradient Descent



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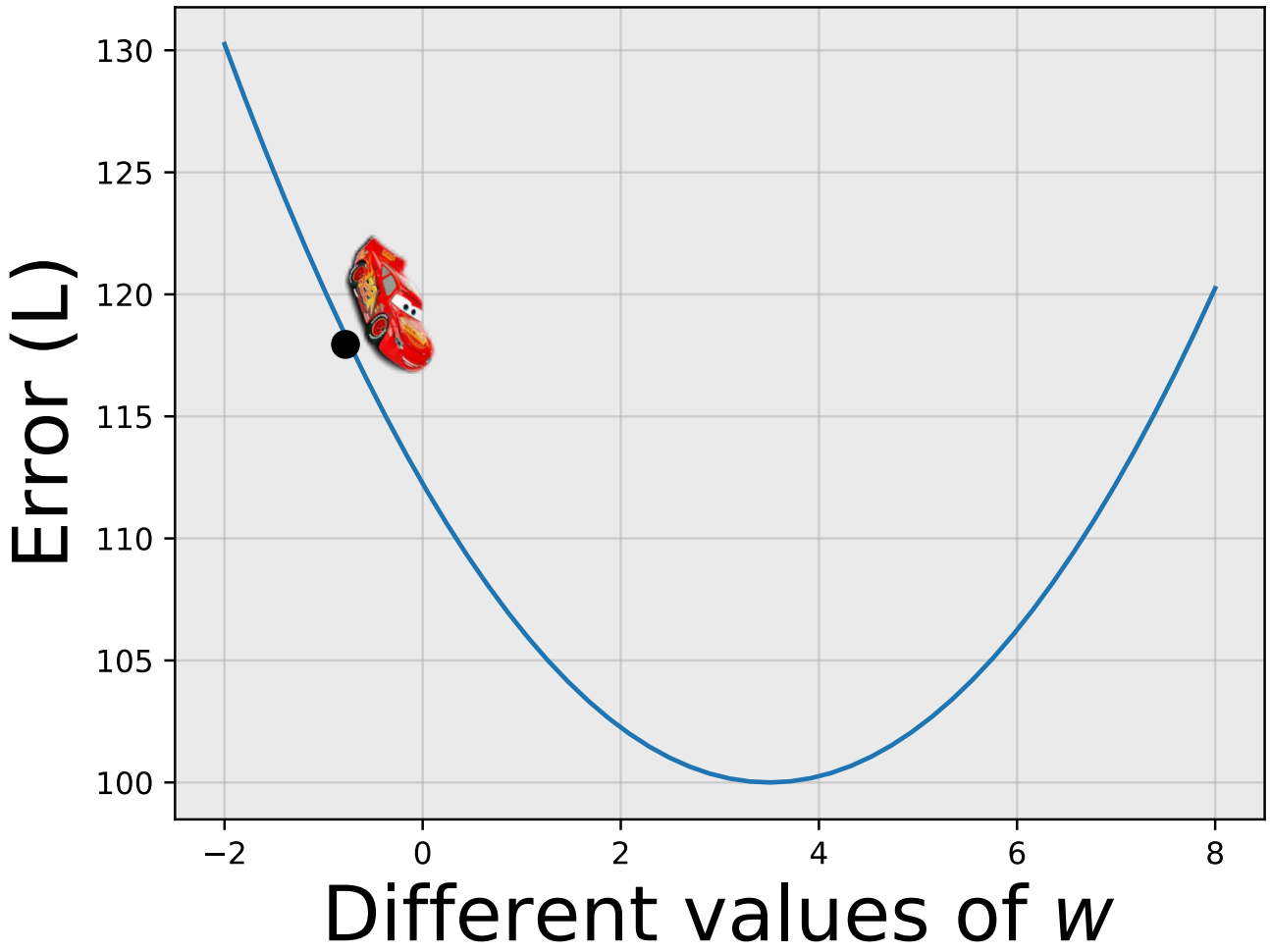

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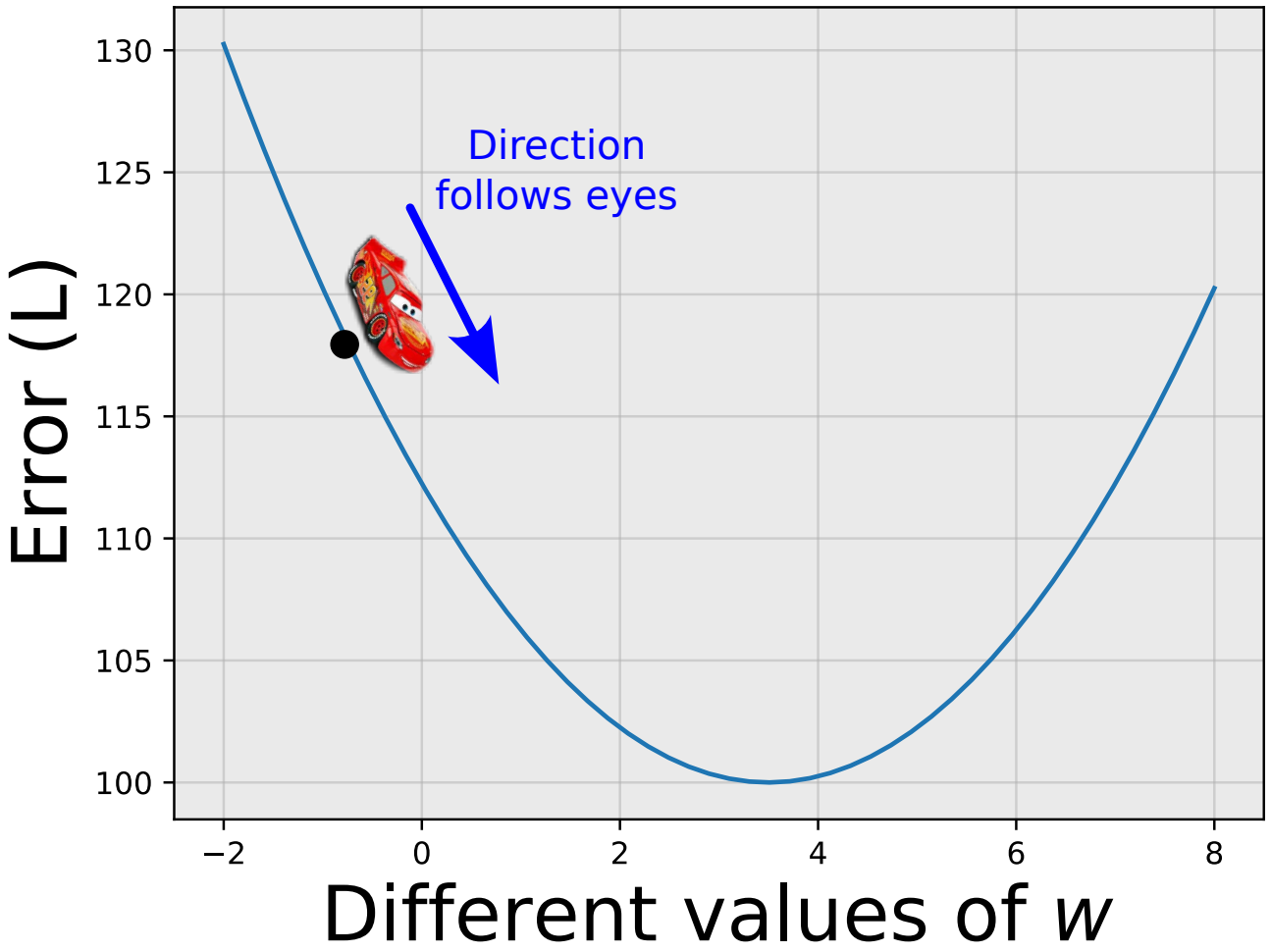

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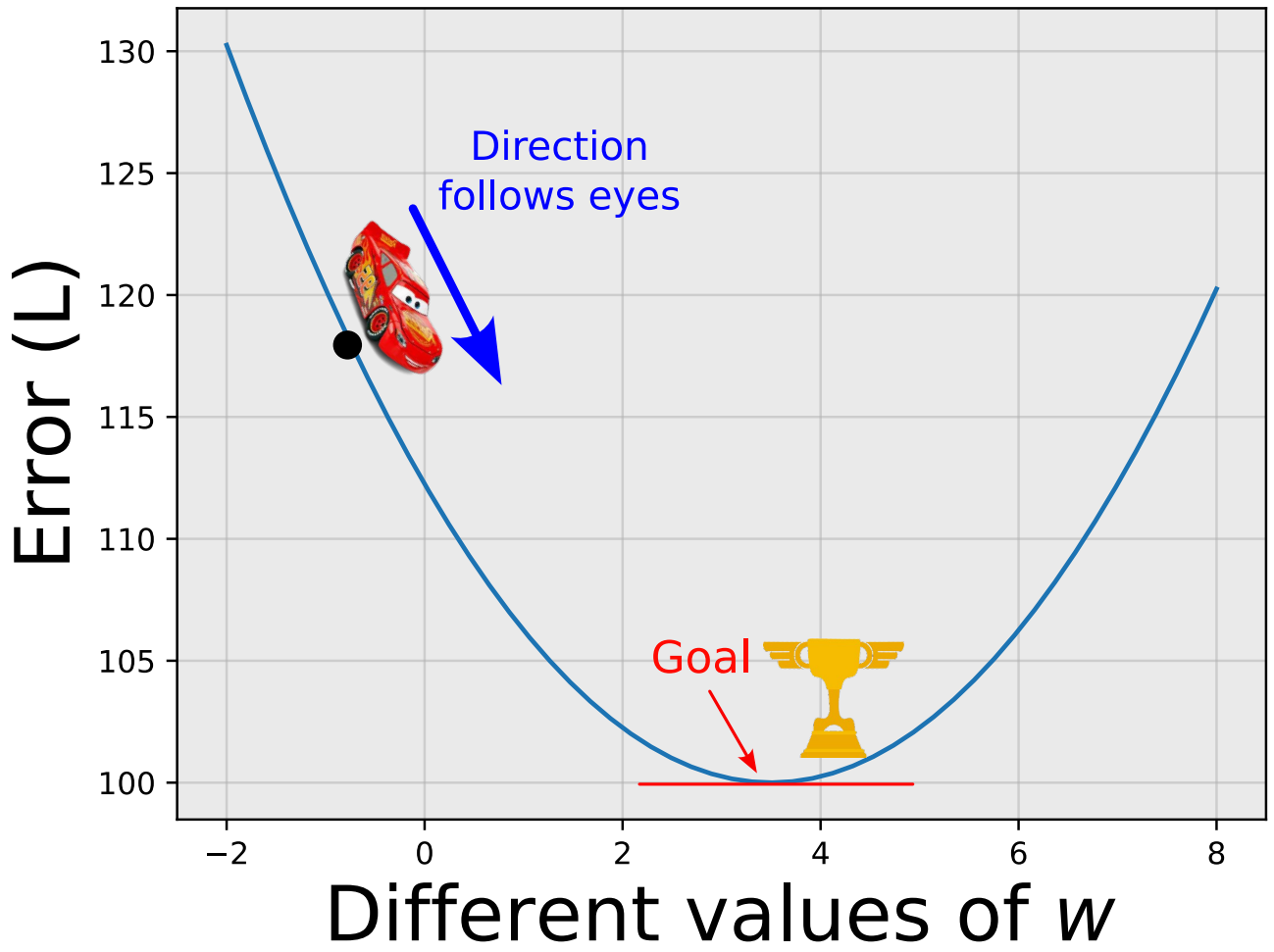

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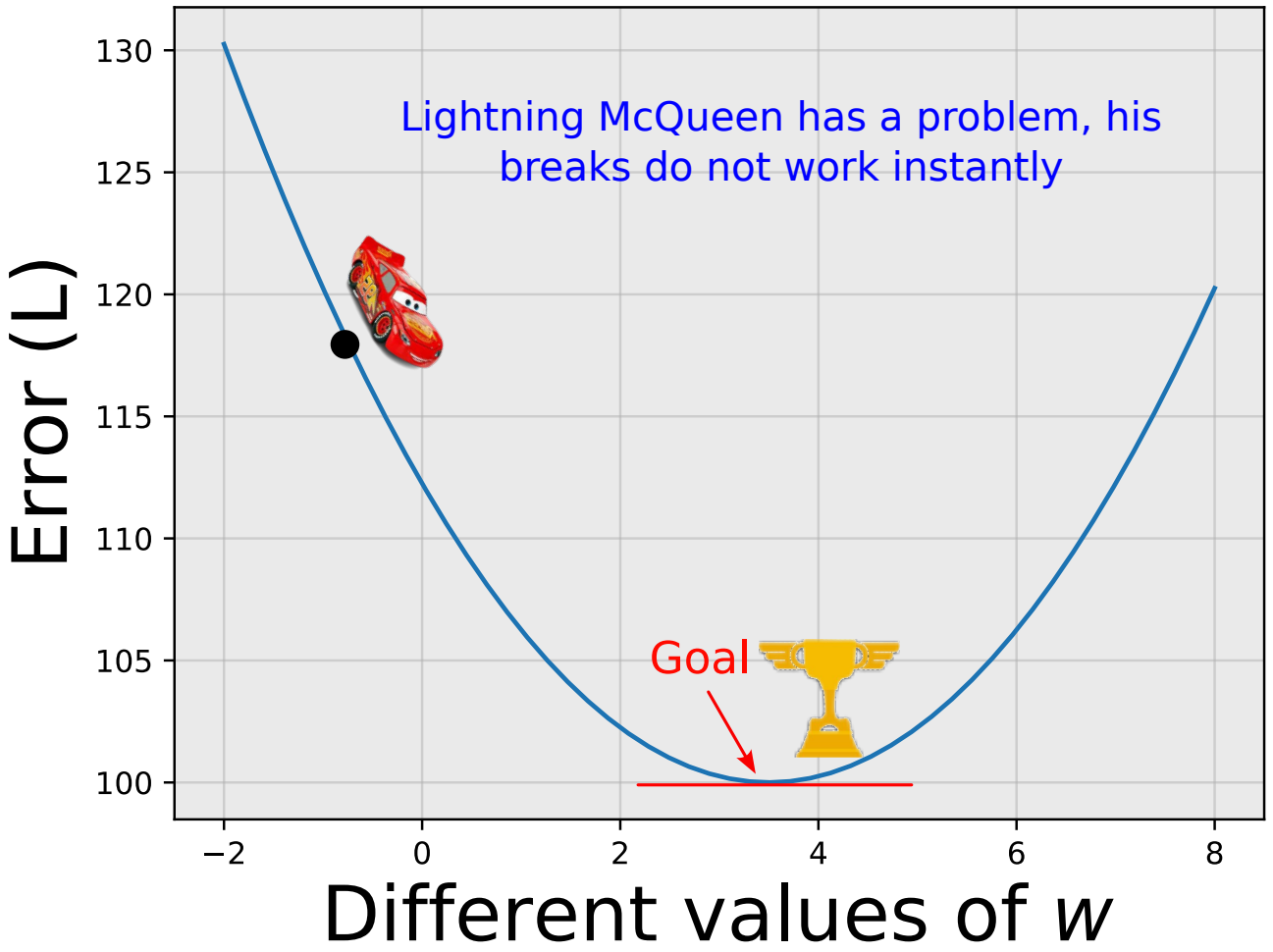

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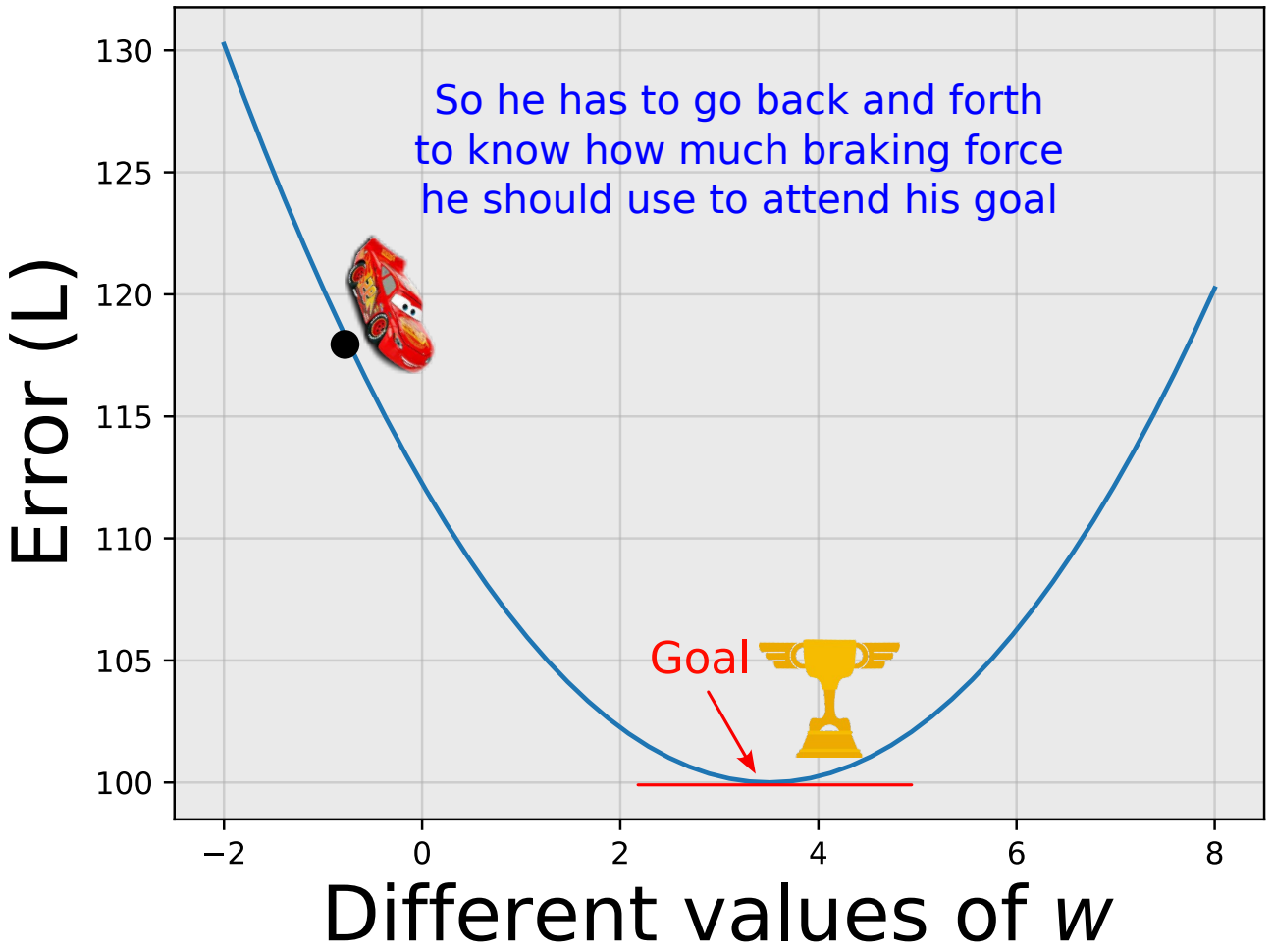

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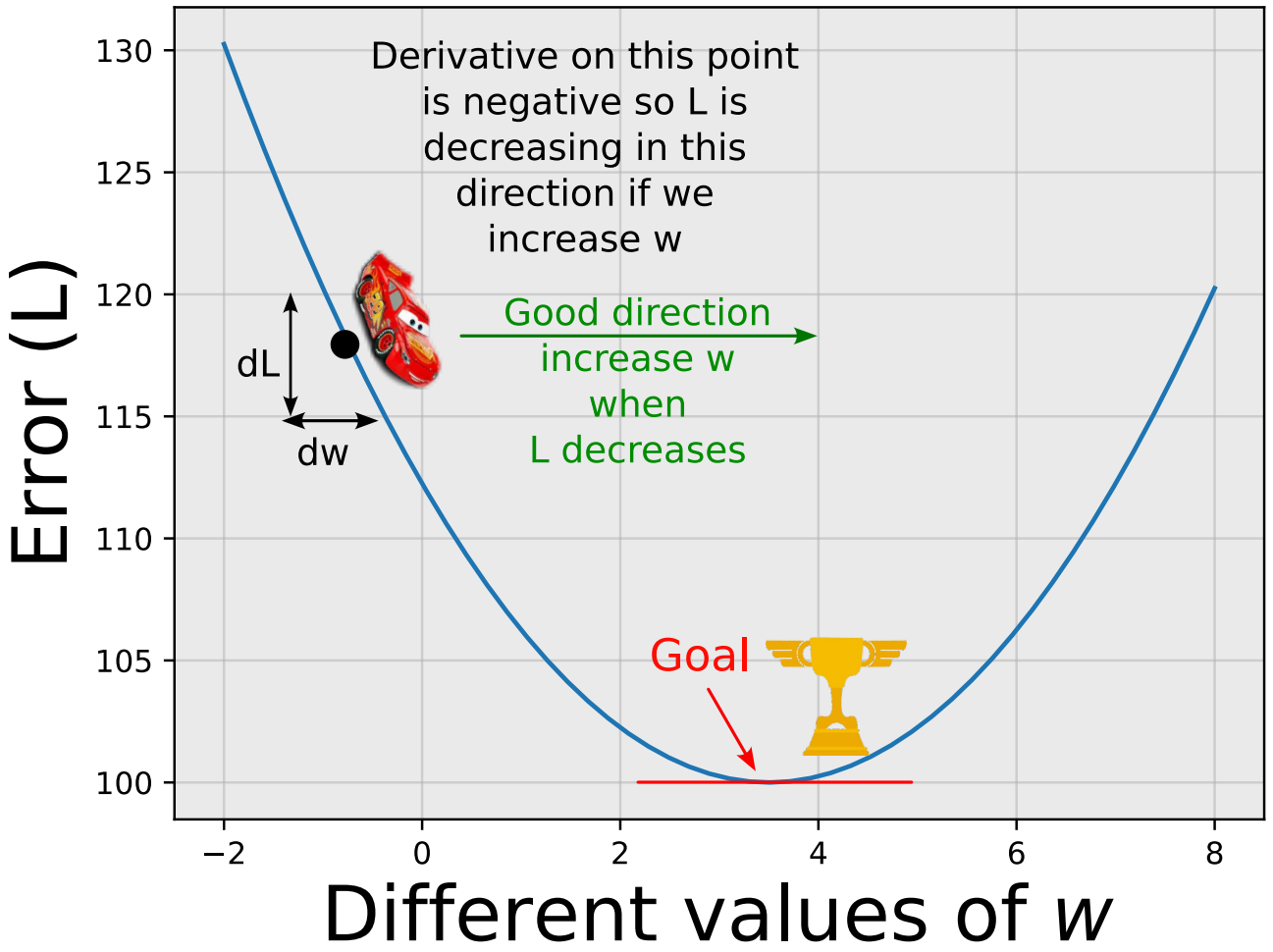

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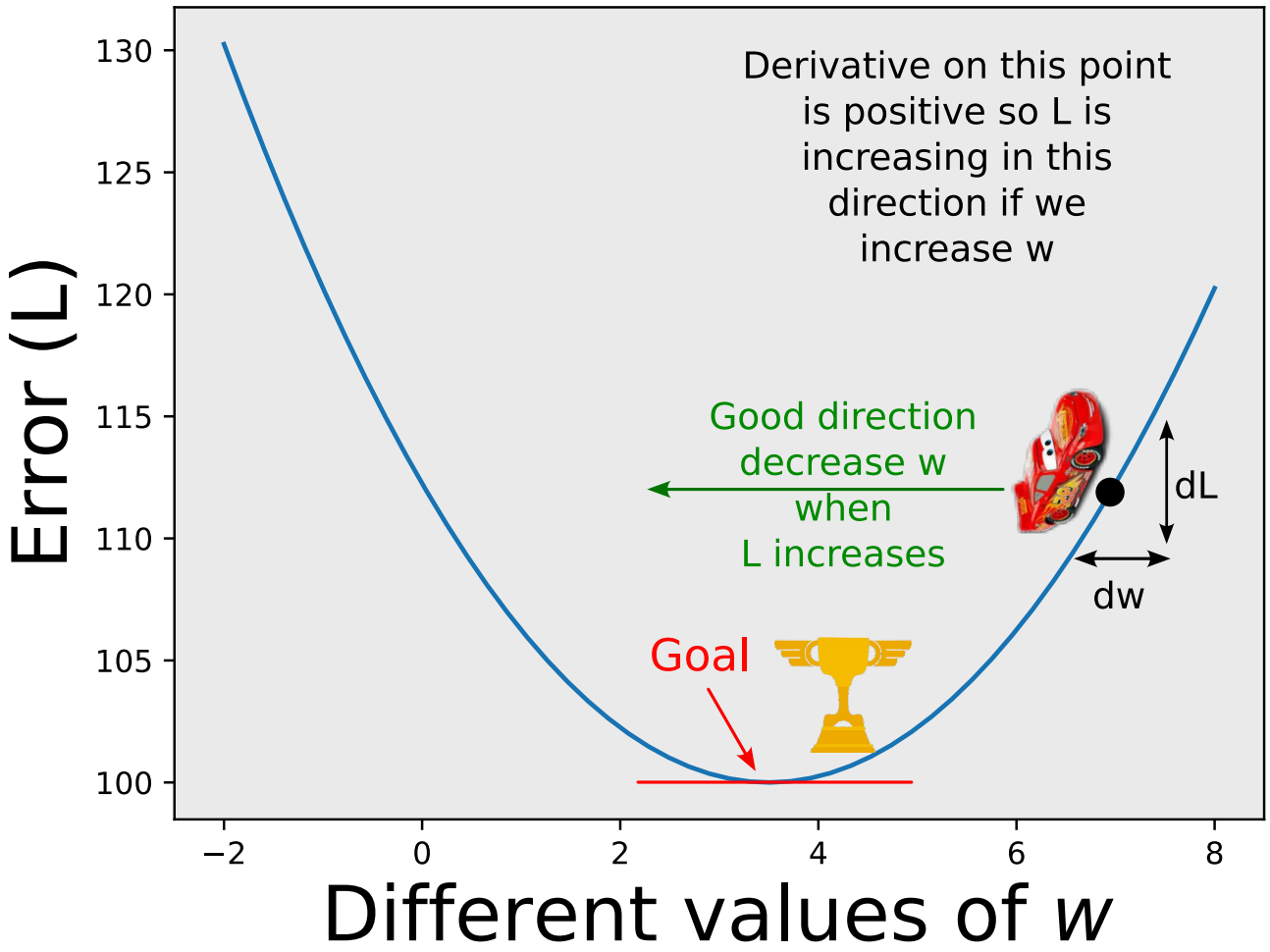


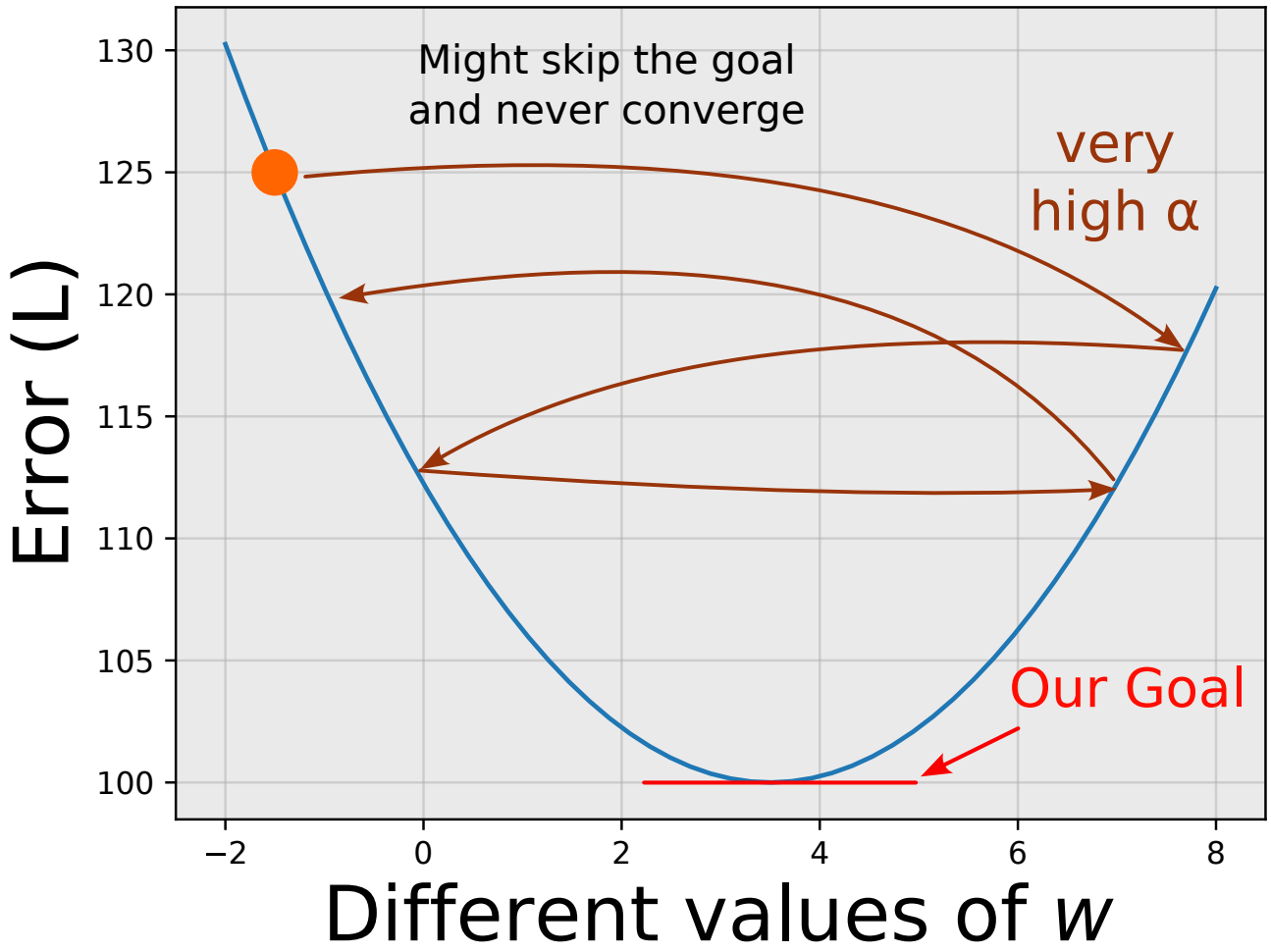
Gradient Descent

How to vaey w in a mathematical formula ?

$$w = w - \alpha \frac{\partial L}{\partial w} \tag{5}$$

- w : the set of parameters to learn
- L : the cost function to minimize
- α : the learning rate that controls the variation of w
- $-$: The minus sign, means that we always vary w in the inverse sign of the gradient of L $\Longleftarrow$ minimize the error

Gradient Descent



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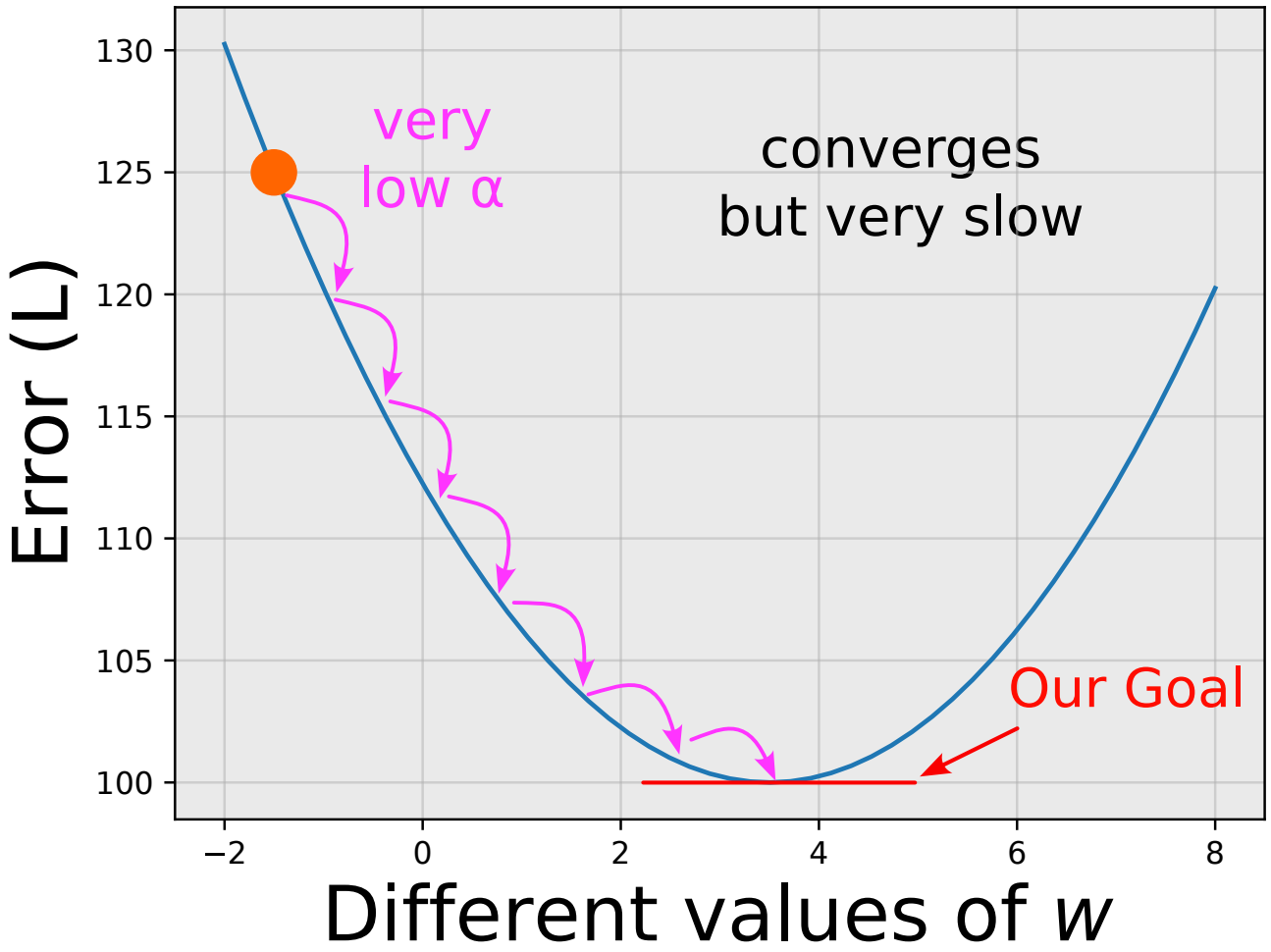

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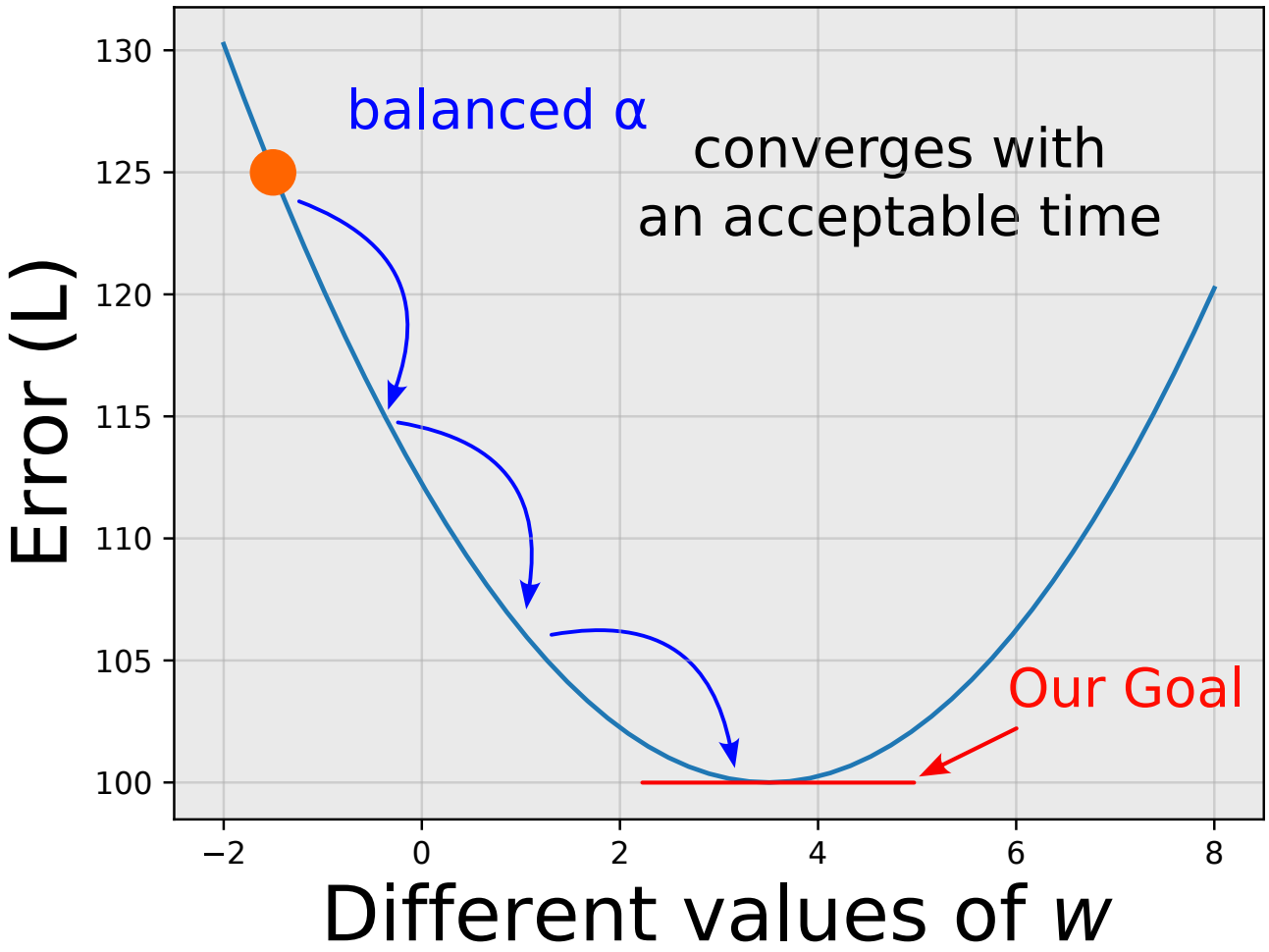

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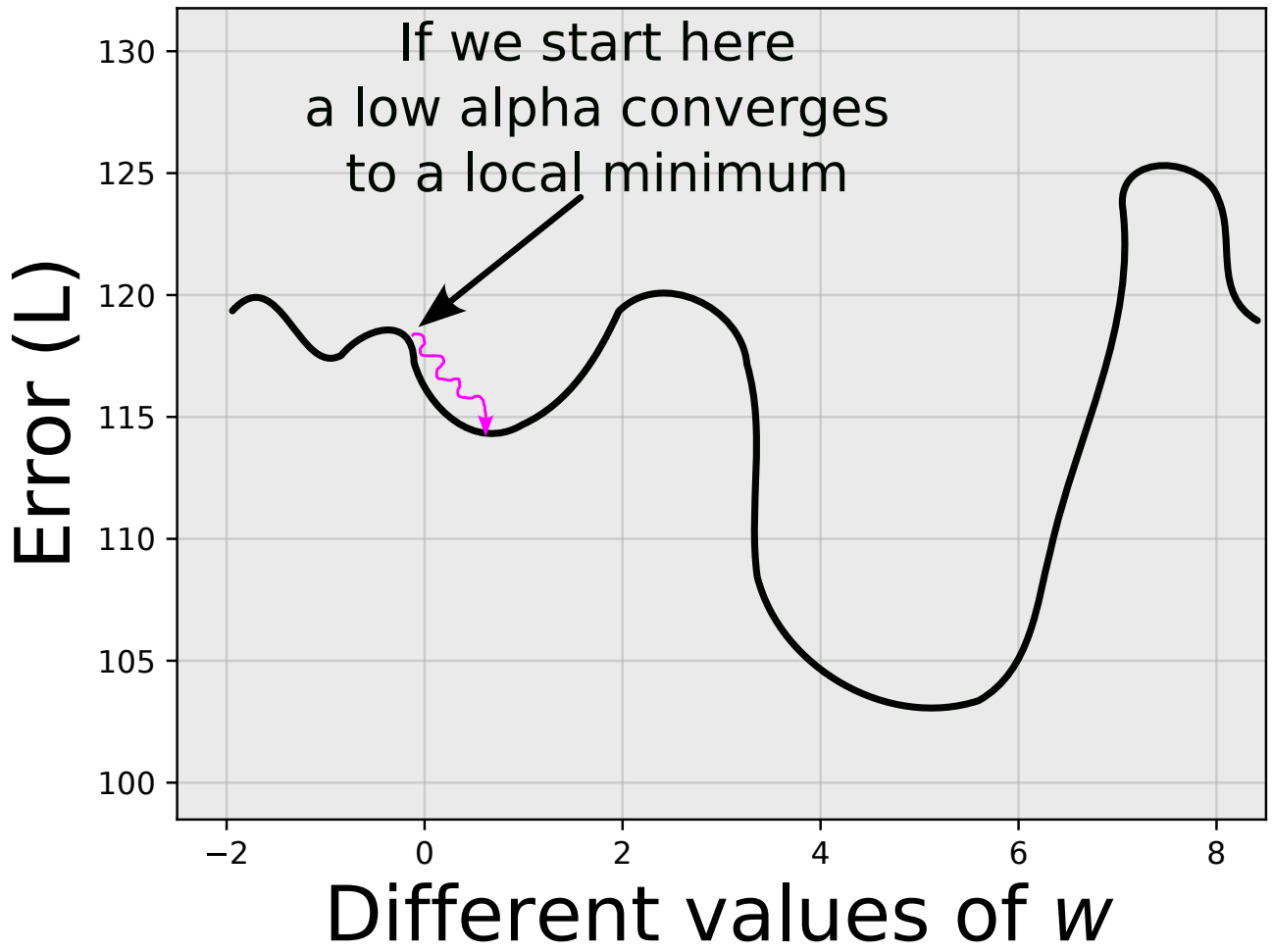

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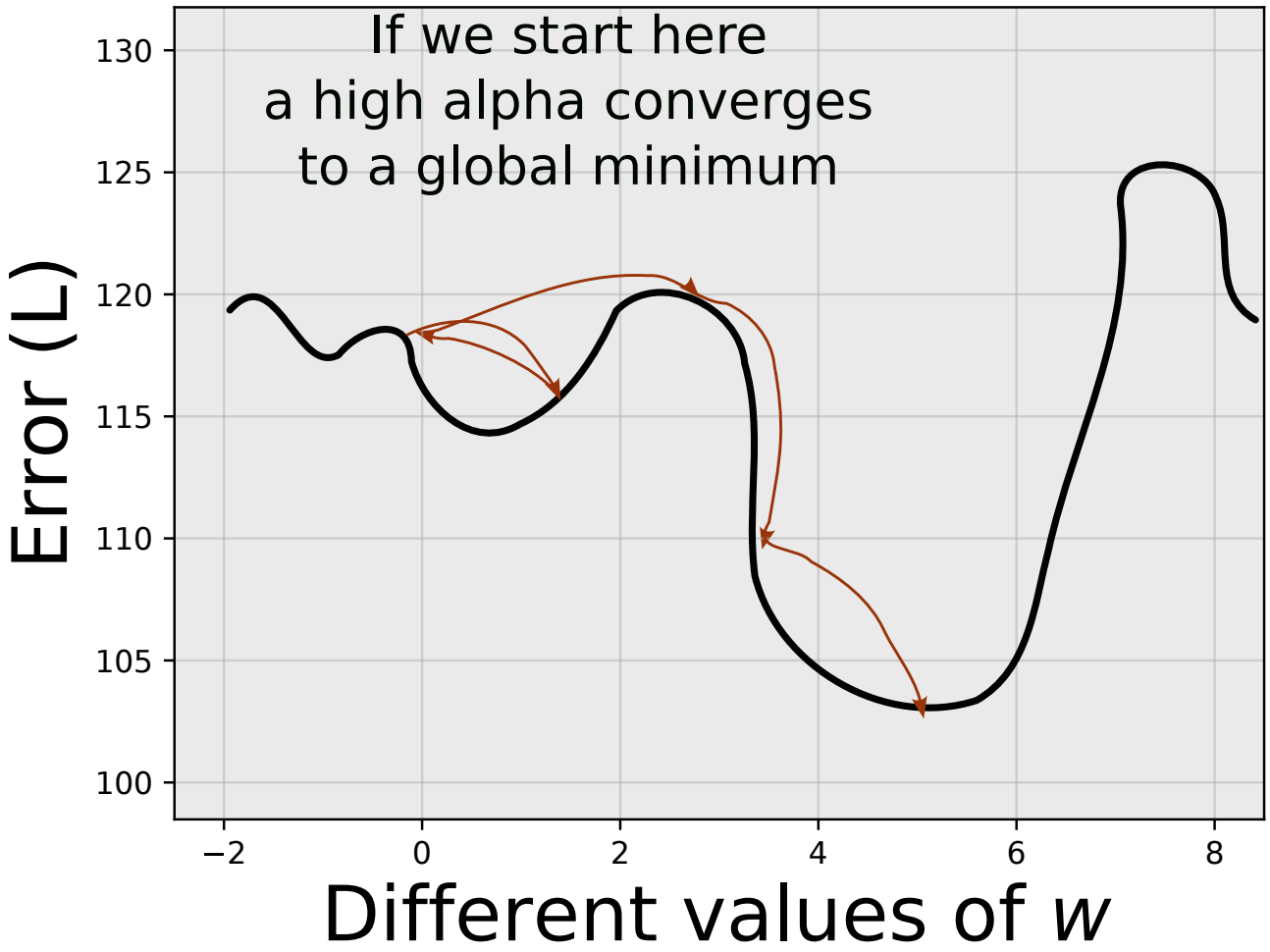

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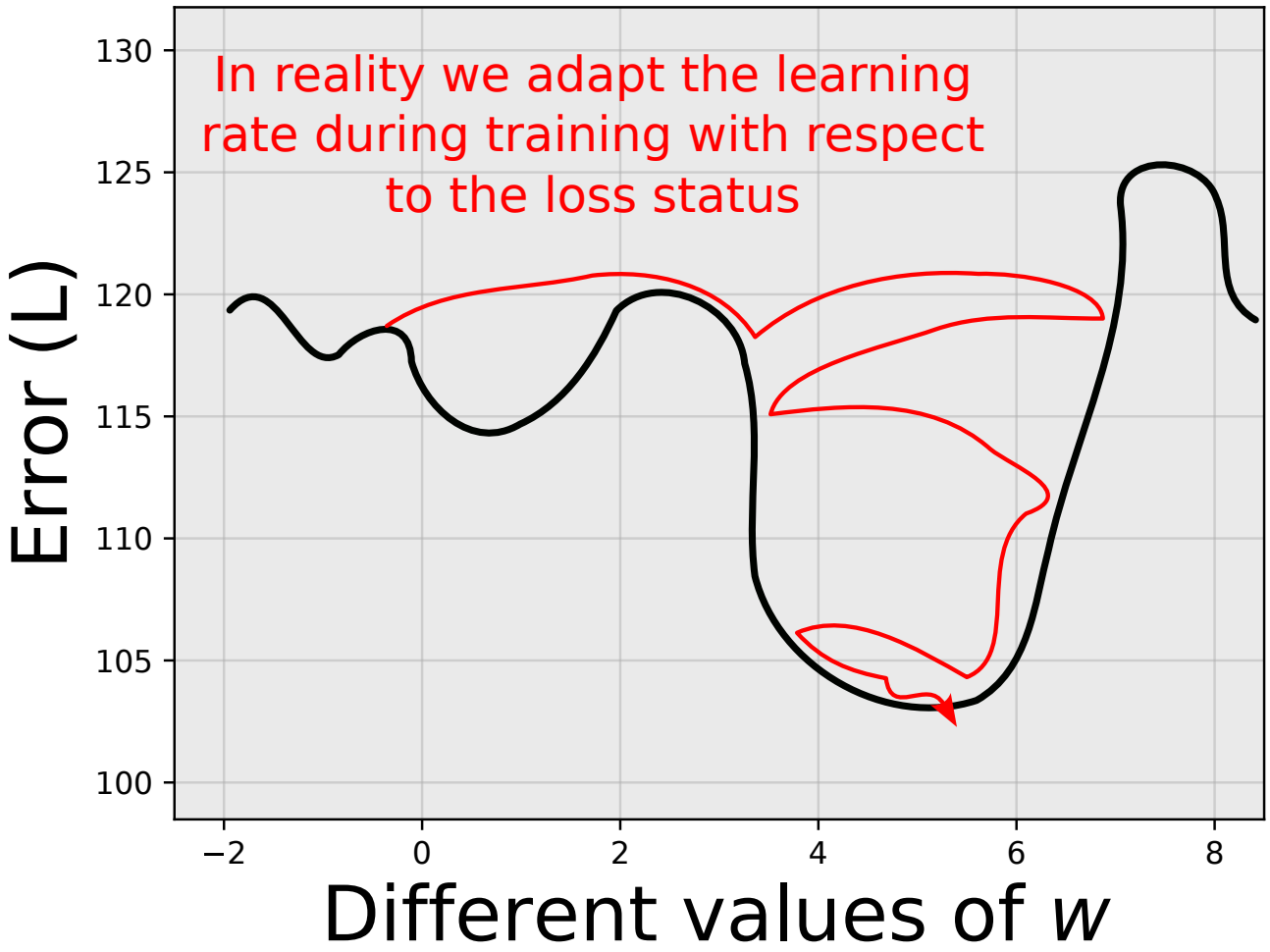

Gradient Descent

Mini-batch learning

- The algorithm "*Batch Gradient Descent*" optimizes the function:

$$L(w) = \frac{1}{n} \sum_{i=1}^{n} error(y_i, \hat{y}_i) \tag{6}$$

- The error should be calculated on all the training set, which is problematic if n is large

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$\Longrightarrow$ "mini-batch" concept

$\Longrightarrow$ calculate L for $m <<< n$

$$L(w) = \frac{1}{m} \sum_{i=s}^{s+m-1} error(y_i, \hat{y}_i) \ \forall \ s \in \{1.m.2m, \ldots, n-m\} \tag{7}$$

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- Once we go through all batches = 1 epoch
- We repeat the procedure many times (many epochs)

Gradient Descent

Pseudo-code for the min-batch gradient descent

Input: X, Y the training dataset
Output: W the parameters that represents the relation $X \implies Y$

Random initialisation of the parameters W

for epoch $= 1 \dots 1000$ **do**

Randomly shuffle the dataset

for each mini-batch X_m, Y_m of size m **do**

$$predictions = model(X_m, W)$$
$$errors = error_function(Y_m, predictions)$$
$$gradient = \frac{\partial L(W)}{\partial W}$$
$$W = W - \alpha.gradient$$

end for

end for

return W

Gradient Descent

Let m be the size of a min-batch

- If $m = n \implies$ Batch Gradient Descent
  - We should calculate the error and gradient on all training examples to change W each epoch

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GD	Update On	Pros	Cons
Batch	Full dataset	Stable, global convergence	Computationally expensive
Stochastic	Single example	Fast convergence, escapes local minima	Noisy updates
Mini-Batch	Mini-batch subset	Balance of stability and speed	Computational overhead

Gradient Descent

https://twitter.com/docmilanfar/status/1755141174313308652?t=0Q6AErLOVIPBfj2smtszJQ

Linear Regression

Linear Regression - Cost Function

General form :

$$L(w) = \frac{1}{n} \sum_{i=1}^{n} erreur(y_i, \hat{y}_i) \tag{8}$$

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Average quadratic error for linear regression

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Average quadratic error for linear regression

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For linear regression, two parameters to learn: w **and** b

Linear Regression - Calculate Gradient with respect to w

$$\frac{\partial L(w,b)}{\partial w} = \frac{\partial(\frac{1}{n}\sum_{i=1}^{n}(y_i - (w.x_i + b))^2)}{\partial w} \tag{11}$$

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Updating w :

$$w = w - \alpha.(-\frac{2}{n}\sum_{i=1}^{n}(x_i(y_i - \hat{y}_i))) \tag{15}$$

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Updating b :

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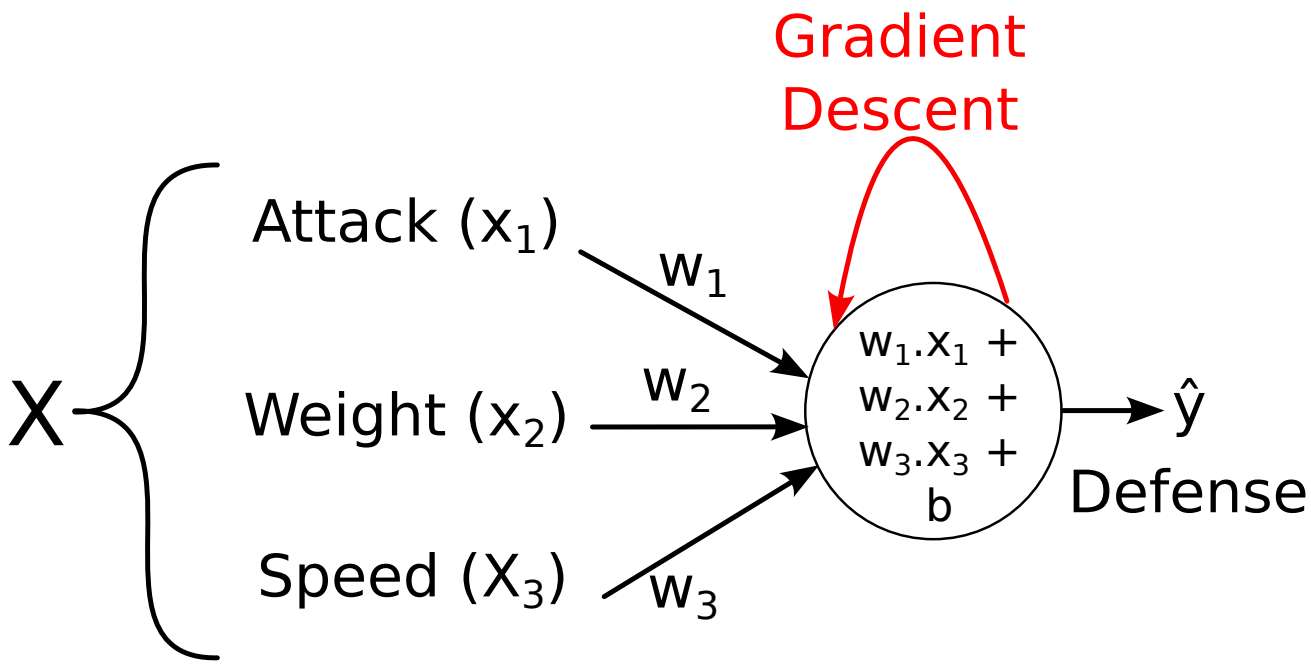
Linear Regression - With Many Variables

If the examples in our dataset have many attributes:

- Example: predict the defense value of a Pokemon in function of its attack value, weight and speed.
- Instead of having one parameter w, we will learn a set of parameters $W = (w_1, w_2, \ldots, w_d)$ for d characteristics in the data
- We repeat the same procedure for every $w_j \in W$
- The linear model becomes: $\hat{y}_i = b + \sum_{j=1}^{d} w_j . x_{i,j}$
- With $x_{i,j}$ being the j_{th} attribute of the i_{th} example in the data

Linear Regression - With Many Variables

Perceptron:



Linear Regression - Normalization of the Data

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$$X_{:,j} = \frac{X_{:,j} - min(X_{:,j})}{max(X_{:,j}) - min(X_{:,j})} \ \forall \ j \in [1, \ldots, d] \tag{21}$$

d being the number of attributes in the dataset

Predicting Defense Values for Pokemon

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name	weight_kg	speed	sp_attack	sp_defense	type
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Charmander	8.5	65	60	50	fire
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Data that is of interest to us:

weight_kg	sp_attack	sp_defense
6.9	65	65
8.5	60	50
32	90	80
9	50	64

- Attributes used to teach the model: weight_kg and sp_attack
- Attribute to predict: sp_defense

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Goal: predict the defense value of a Pokemon in function of 2 attributes

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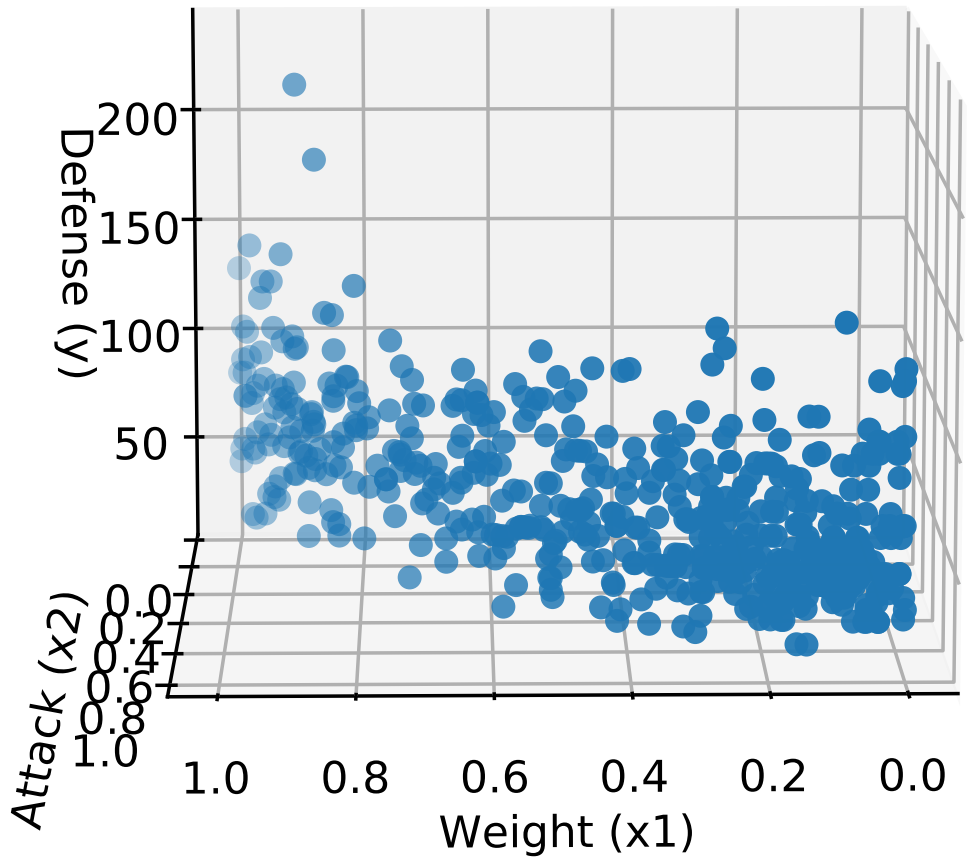
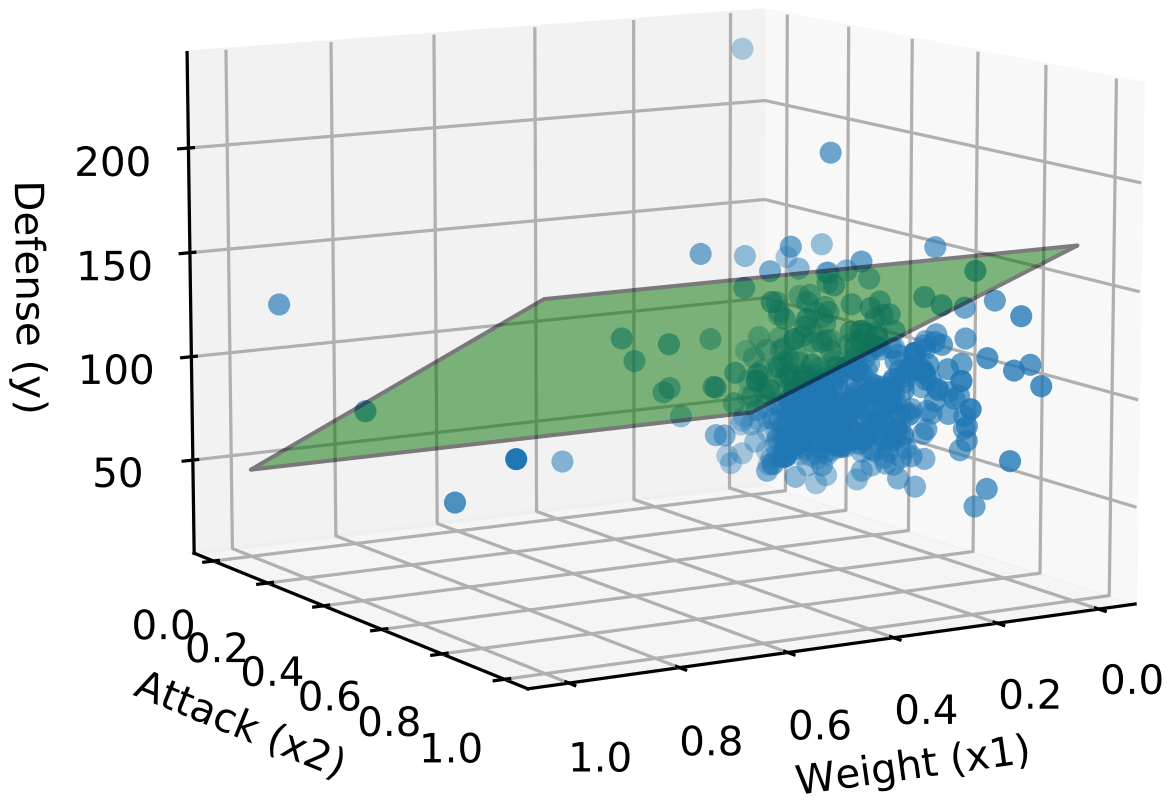
3D plot of the data



Predicting Defense Values for Pokemon

3D plot of data with decision plane



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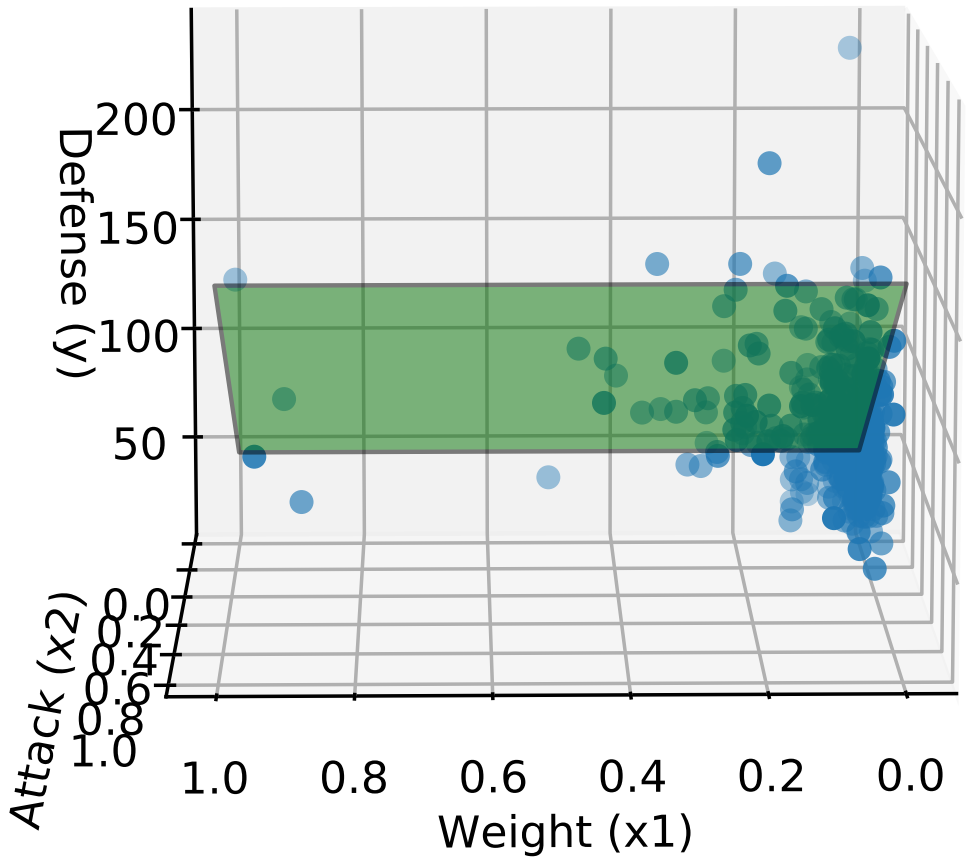

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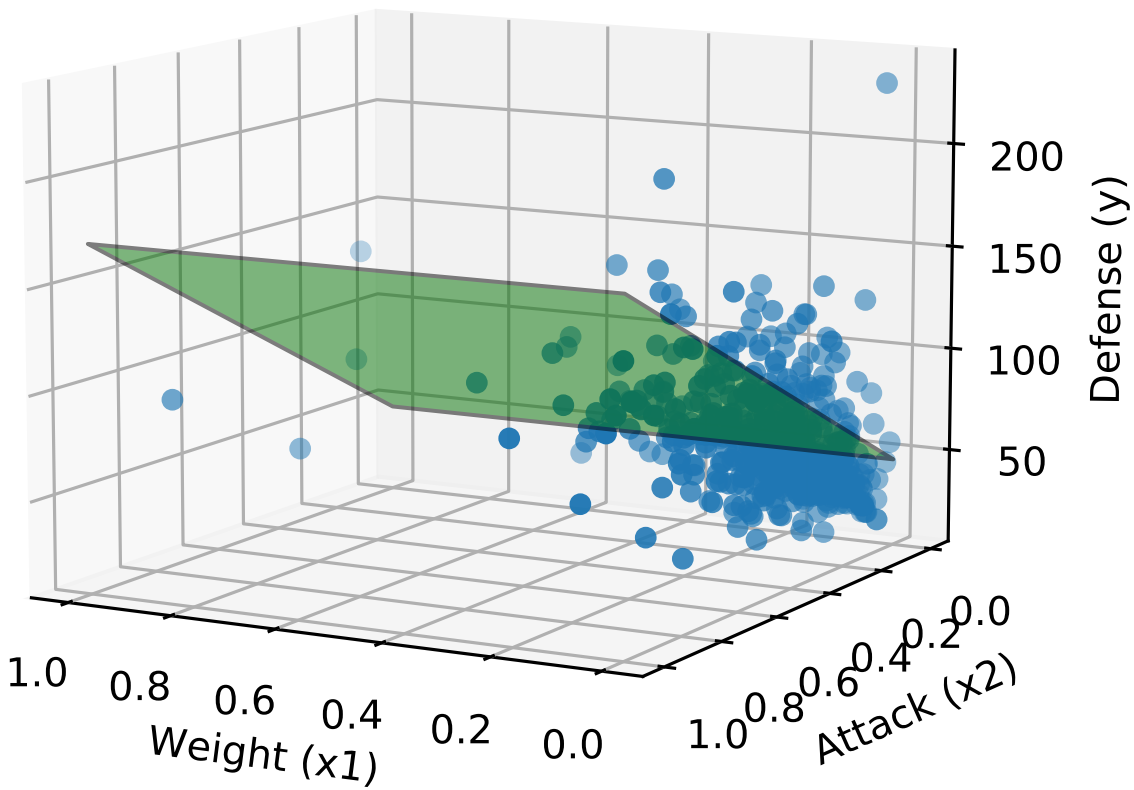

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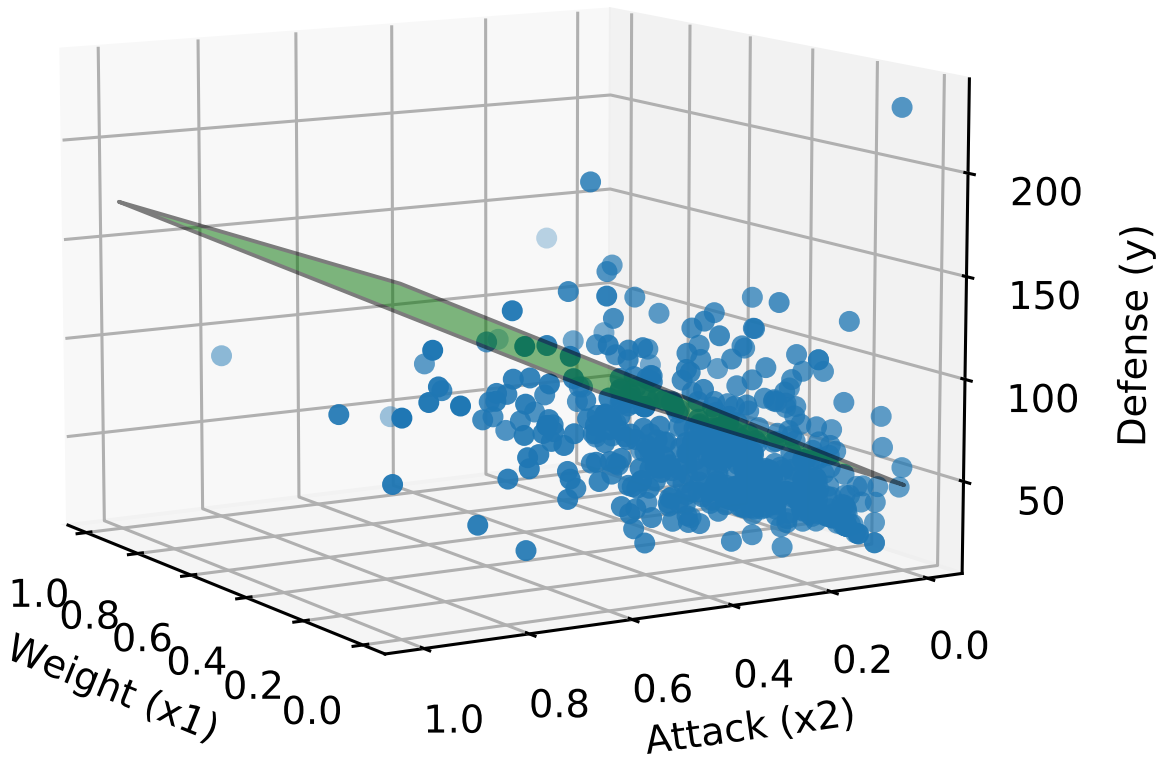

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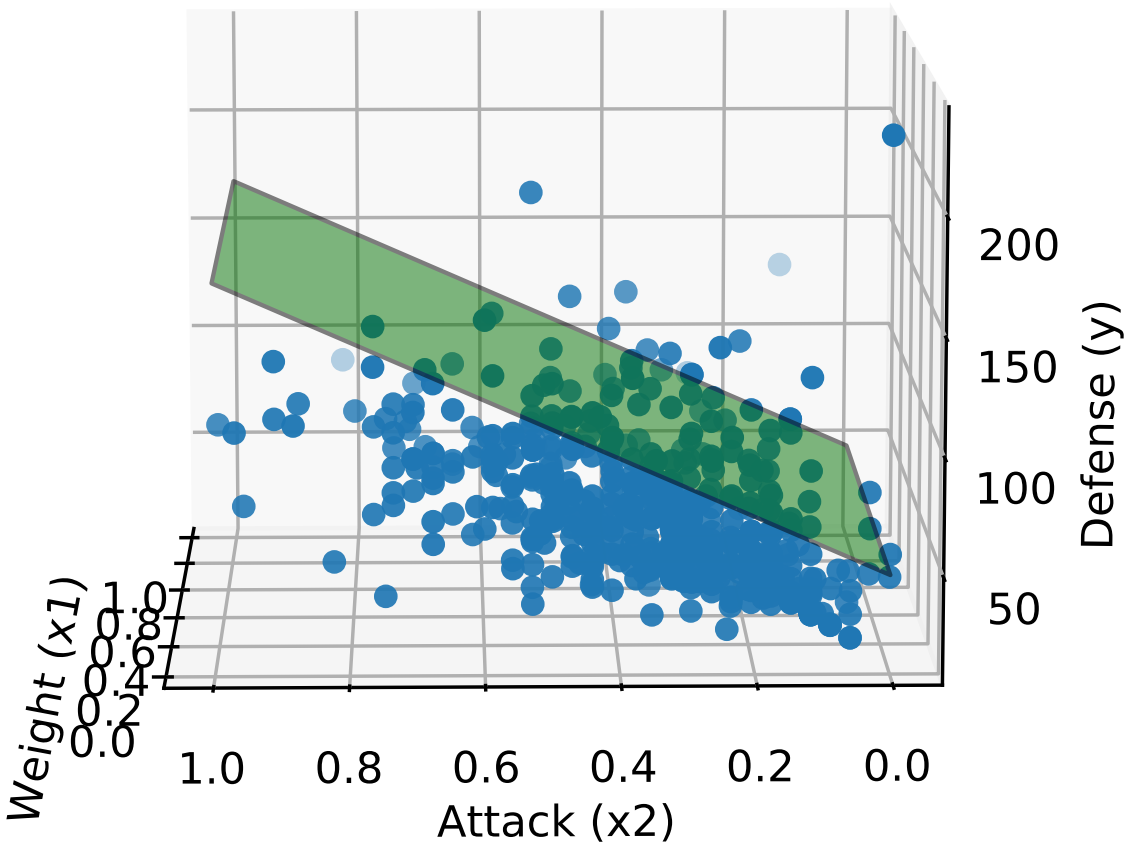
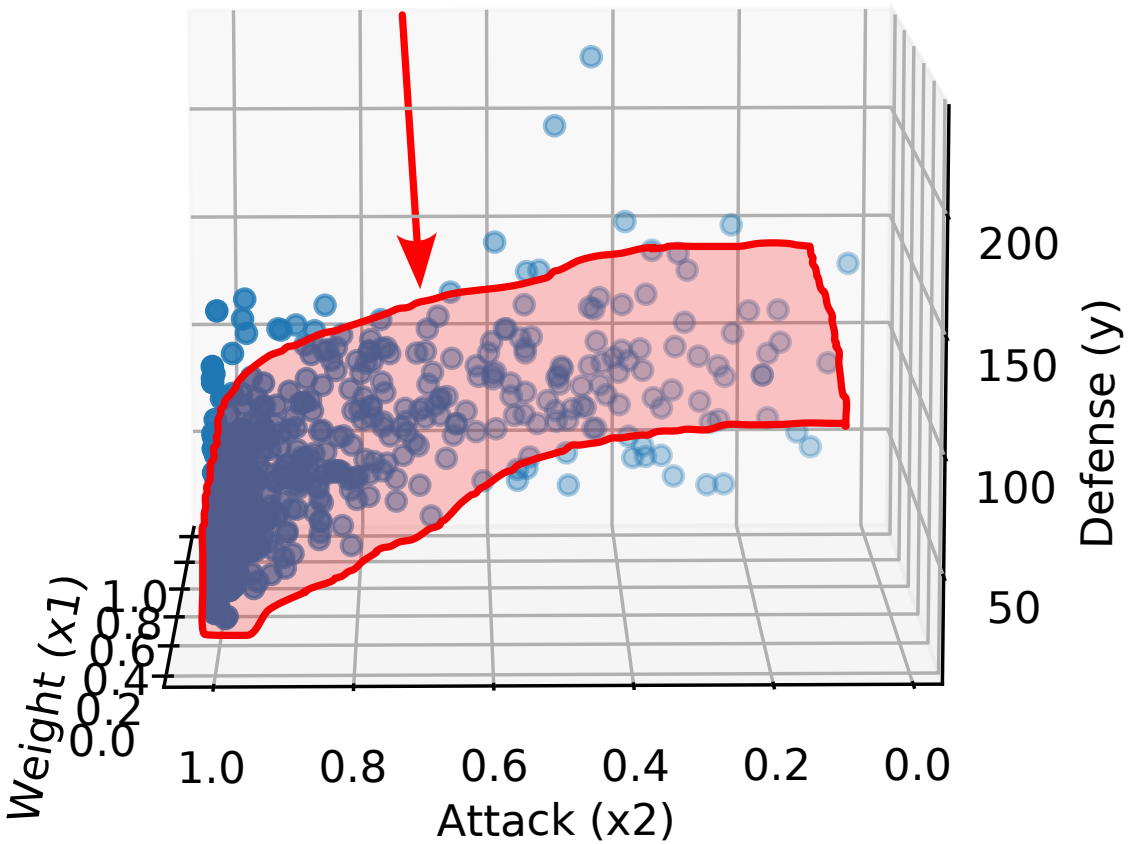


Predicting Defense Values for Pokemon

Is linear decision the best approach ?

seems to be a curved plane
so non-linear decision



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