

DSC 140A

Probabilistic Modeling & Machine Learning

Lecture 3 | Part 1

Recap

Empirical Risk

- ▶ Last time, we framed the problem of learning as **minimizing** the **empirical risk**.

$$R(H) = \frac{1}{n} \sum_{i=1}^n \ell(H(\vec{x}^{(i)}), y_i)$$

- ▶ In the case where H is linear::

$$R(\vec{w}) = \frac{1}{n} \sum_{i=1}^n \ell(\vec{w} \cdot \text{Aug}(\vec{x}^{(i)}), y_i)$$

Minimizing Empirical Risk

- ▶ Picking different loss functions changes the optimization problem.
- ▶ If we use **square loss**:

$$R(\vec{w}) = \frac{1}{n} \sum_{i=1}^n (\vec{w} \cdot \text{Aug}(\vec{x}^{(i)}) - y_i)^2$$

- ▶ We can minimize by setting the gradient to zero.
- ▶ We get: $\vec{w} = (X^T X)^{-1} X^T \vec{y}$.

Minimizing Empirical Risk

- ▶ But sometimes we can't use this approach.
 - ▶ If R is not differentiable (absolute loss).
 - ▶ If computing $\vec{w}^* = (X^T X)^{-1} X^T \vec{y}$ is too expensive.
 - ▶ ...

Today

- ▶ A general, very popular approach to optimization: **gradient descent**.
- ▶ Instead of solving for \vec{w}^* “all at once”, we’ll iterate towards it.

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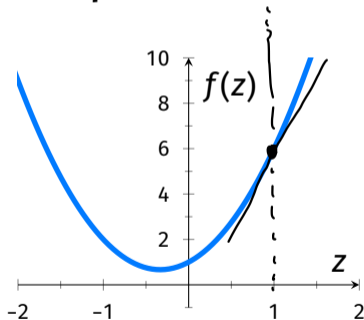
Probabilistic Modeling & Machine Learning

Lecture 3 | Part 2

What is the gradient?

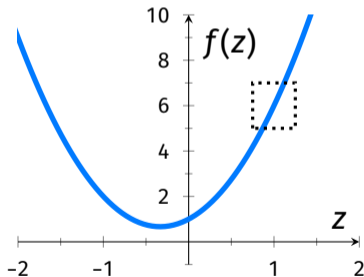
What is the derivative?

- ▶ Consider $f(z) = 3z^2 + 2z + 1$.
 - ▶ What is the **slope** of the curve at $z = 1$?



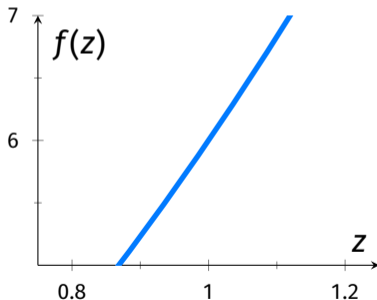
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What is the derivative?

- ▶ The **derivative** gives the slope anywhere:

$$f(z) = 3z^2 + 2z + 1$$

$$\frac{df}{dz}(z) = 6z + 2$$

The slope of the curve at $z = 1$:

$$\frac{df}{dz}(1) = 6 \cdot 1 + 2 = 8$$

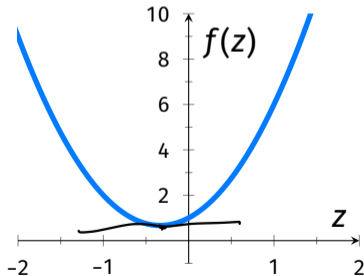
What type of object?

- ▶ The derivative of $f : \mathbb{R} \rightarrow \mathbb{R}$ is a **function**:
 - ▶ Input: scalar.
 - ▶ Output: scalar.
 - ▶ Example: $\frac{df}{dz}(z) = 6z + 2$.

- ▶ The derivative **evaluated at a point** is a **scalar**:
 - ▶ Example: $\frac{df}{dz}(1) = 8$.

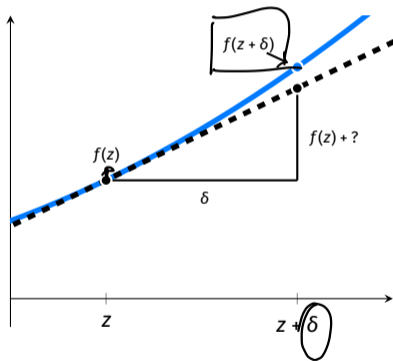
Sign of the Derivative

- ▶ If the derivative at a point is:
 - ▶ Positive: the function is **increasing**.
 - ▶ Negative: the function is **decreasing**.
 - ▶ Zero: the function is **flat**.



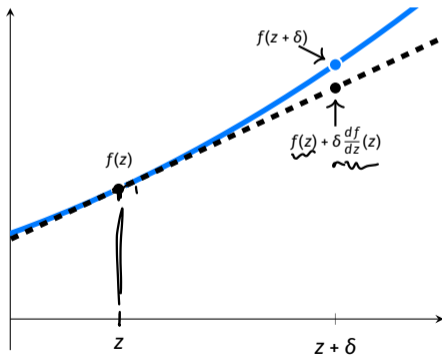
Exercise

What is the height of the dashed line at $z + \delta$?



Derivatives and Change

- ▶ The derivative tells us **how much** the function changes with an infinitesimal increase in z .

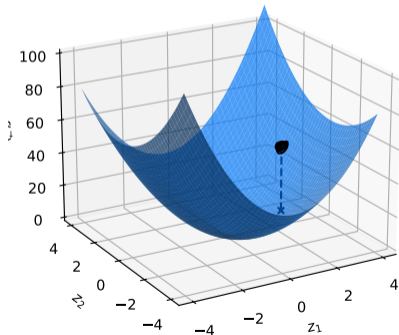


Increases and Decreases

- ▶ The sign of the derivative tells us if the function is increasing or decreasing.
 - ▶ Positive: f is increasing at z .
 - ▶ Negative: f is decreasing at z .

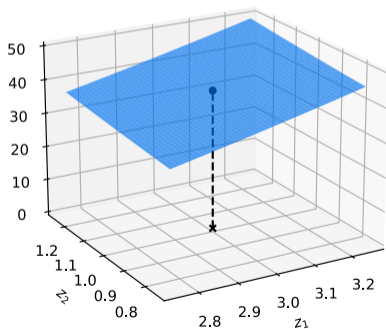
Multivariate Functions

- ▶ Now consider $f(\vec{z}) = f(z_1, z_2) = 4z_1^2 + 2z_2 + 2z_1z_2$.
 - ▶ What is the **slope** of the surface at $(z_1, z_2) = (3, 1)$?



Multivariate Functions

- ▶ Now consider $f(\vec{z}) = f(z_1, z_2) = 4z_1^2 + 2z_2 + 2z_1z_2$.
 - ▶ What is the **slope** of the surface at $(z_1, z_2) = (3, 1)$?



Partial Derivatives

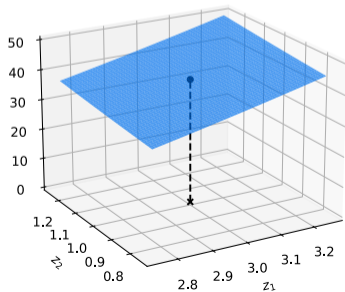
- ▶ When f is a function of a vector $\vec{z} = (z_1, z_2)^T$, there are **two** slopes to talk about:
- ▶ $\frac{\partial f}{\partial z_1}$: slope in the z_1 direction.
- ▶ $\frac{\partial f}{\partial z_2}$: slope in the z_2 direction.

Example

What is the slope of f at $(z_1, z_2) = (3, 1)$ in:

- ▶ The z_1 direction?
- ▶ The z_2 direction?

$$f(\vec{z}) = 4z_1^2 + 2z_2 + 2z_1z_2$$



- ▶ $\frac{\partial f}{\partial z_1}(z_1, z_2) = 8z_1 + 2z_2$
- ▶ $\frac{\partial f}{\partial z_1}(3, 1) = 8 \cdot 3 + 2 \cdot 1 = 26$
- ▶ $\frac{\partial f}{\partial z_2}(z_1, z_2) = 2z_2 + 2z_1$
- ▶ $\frac{\partial f}{\partial z_2}(3, 1) = 2 \cdot 3 + 2 \cdot 1 = 8$

What is the gradient?

- ▶ We can package the partial derivatives into a single object: the **gradient**.

$$\frac{df}{d\vec{z}}(\vec{z}) = \begin{pmatrix} \frac{\partial f}{\partial z_1}(\vec{z}) \\ \frac{\partial f}{\partial z_2}(\vec{z}) \end{pmatrix}$$

What is the gradient?

- ▶ In general, if $f : \mathbb{R}^d \rightarrow \mathbb{R}$, then the gradient is:

$$\frac{df}{d\vec{z}}(\vec{z}) = \begin{pmatrix} \frac{\partial f}{\partial z_1}(\vec{z}) \\ \frac{\partial f}{\partial z_2}(\vec{z}) \\ \vdots \\ \frac{\partial f}{\partial z_d}(\vec{z}) \end{pmatrix}$$

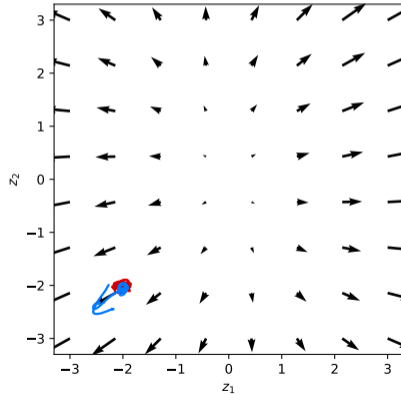
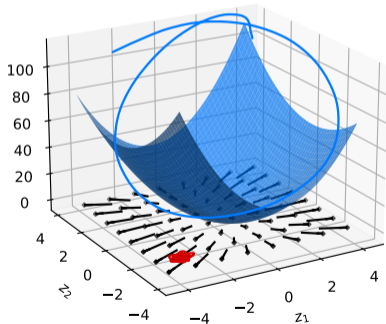
What type of object?

- ▶ The gradient of a function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is a **function**¹:
 - ▶ Input: vector in \mathbb{R}^d .
 - ▶ Output: vector in \mathbb{R}^d .
 - ▶ Example: $\frac{df}{d\vec{z}}(\vec{z}) = (8z_1 + 2z_2, 2 + 2z_1)^T$.
- ▶ The gradient of $f : \mathbb{R}^d \rightarrow \mathbb{R}$ **evaluated at a point** is a **vector** in \mathbb{R}^d :
 - ▶ Example: $\frac{df}{d\vec{z}}(3, 1) = (26, 8)^T$.

¹Sometimes it is referred to as a **vector field**.

Gradient Fields

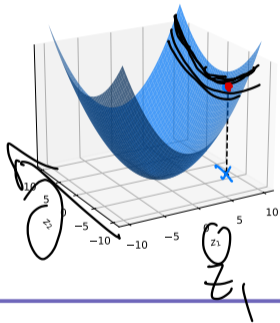
- ▶ The gradient can be viewed as a **vector field**:



Meaning of Gradient Vector

- ▶ The gradient of a function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ at a point \vec{z} is a vector in \mathbb{R}^d .
- ▶ The i th component is the **slope** of f at \vec{z} in the i th direction.

Exercise



Which of these could possibly be the gradient at the point $(9, -4)$?

- ▶ A) $(0, 0)$
- ▶ B) $(4, -1)$
- ▶ C) $(-4, -1)$
- ▶ D) $(-4, 1)$

Gradients and Change

► Recall: $f(z + \delta) \approx \underbrace{f(z)} + \underbrace{\delta}_{\text{m}} \times \underbrace{\frac{df}{dz}(z)}.$

► In multiple dimensions:

$$f(\vec{z} + \vec{\delta}) \approx \underbrace{f(\vec{z})} + \underbrace{\left(\delta_1 \times \frac{\partial f}{\partial z_1}(\vec{z}) \right)}_{\text{product}} + \underbrace{\left(\delta_2 \times \frac{\partial f}{\partial z_2}(\vec{z}) \right)} + \dots$$
$$\approx \underbrace{f(\vec{z}) + \vec{\delta} \cdot \frac{df}{d\vec{z}}(\vec{z})}$$

$$f(\vec{z} + \underline{\delta}) \approx f(\vec{z}) + \underline{\delta} \cdot \frac{df}{d\vec{z}} = 7 + \begin{pmatrix} .1 \\ .1 \end{pmatrix} \cdot \begin{pmatrix} 4 \\ -2 \end{pmatrix}$$

$$7 + \begin{pmatrix} .1 \\ .1 \end{pmatrix} \cdot \begin{pmatrix} 4 \\ -2 \end{pmatrix} = 7 + (.4) - .2 = 7 + .2 = 7.2$$

Exercise

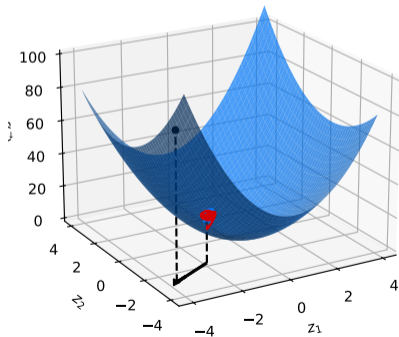
At a point $\vec{z} = (2, 3)^T$, $f(\vec{z})$ is 7 and the gradient $\frac{df}{d\vec{z}}(\vec{z}) = (4, -2)^T$.

What is the approximate^a value of $f(2.1, 3.1)$?

^aQuality of approximation depends on second derivative.

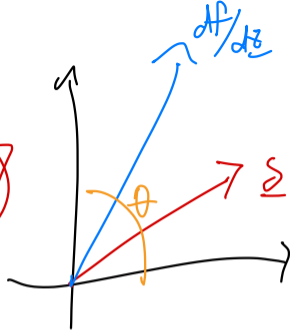
Steepest Ascent

- ▶ **Key property:** the gradient vector points in the direction of **steepest ascent**.



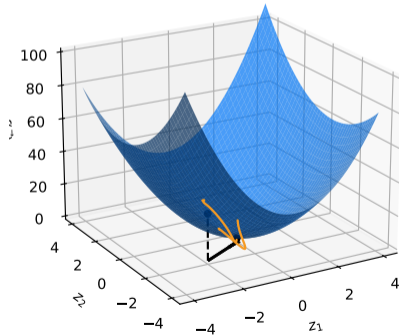
Proof

- ▶ Remember: $f(\vec{z} + \vec{\delta}) \approx f(\vec{z}) + \vec{\delta} \cdot \frac{df}{d\vec{z}}(\vec{z})$.
- ▶ So the total change is $\vec{\delta} \cdot \frac{df}{d\vec{z}}(\vec{z})$.
- ▶ Also remember: $\vec{\delta} \cdot \frac{df}{d\vec{z}}(\vec{z}) = \|\vec{\delta}\| \left\| \frac{df}{d\vec{z}}(\vec{z}) \right\| \cos \theta$.
- ▶ So the increase in f is maximized when $\theta = 0$.
 - ▶ That is, when $\vec{\delta}$ points in the direction of $\frac{df}{d\vec{z}}(\vec{z})$.



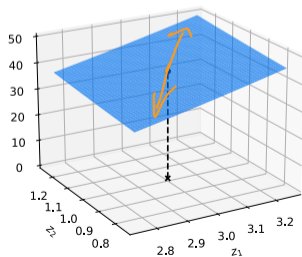
Steepest Descent

- ▶ The **negative** gradient points in the direction of **steepest descent**.

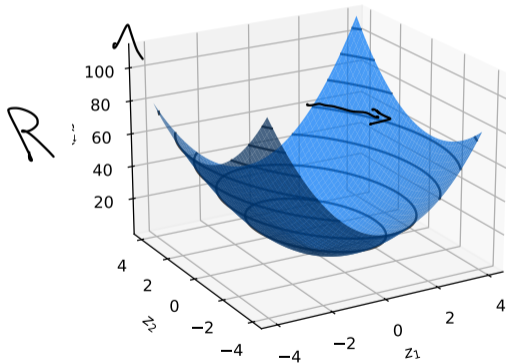


Why?

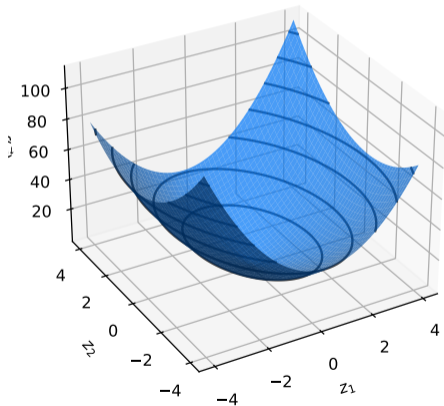
- ▶ The direction of steepest ascent is the **opposite** of the direction of steepest descent.
- ▶ Because, zoomed in, the function looks linear.



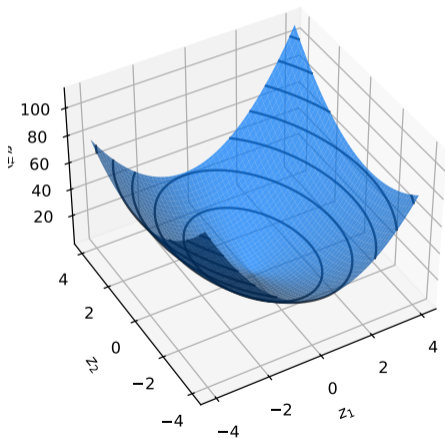
Contours (level curves)



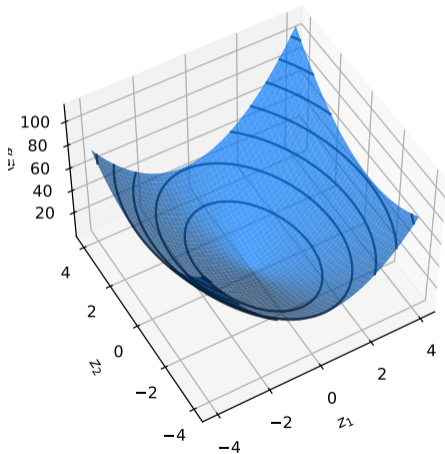
Contours



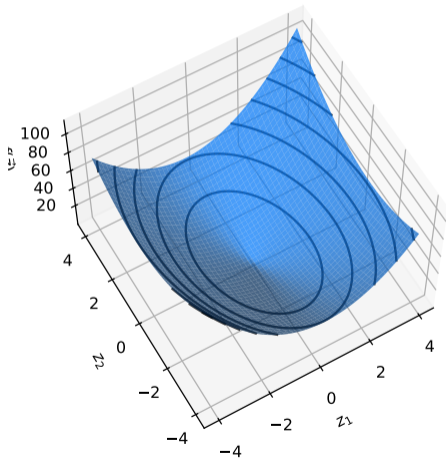
Contours



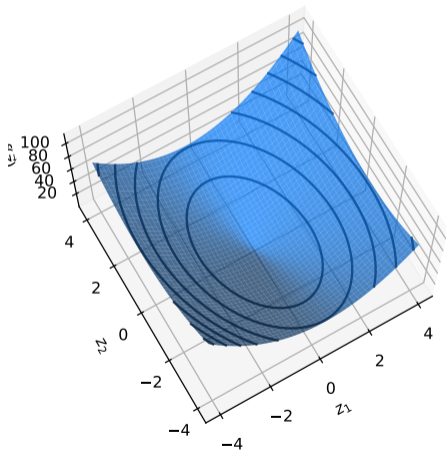
Contours



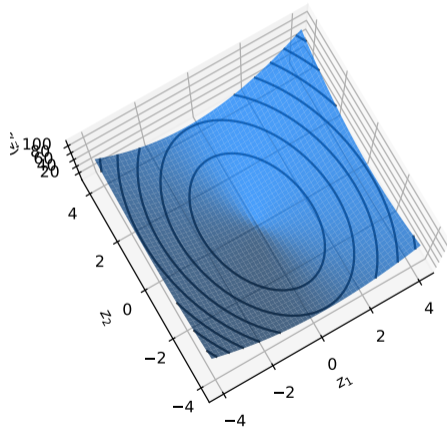
Contours



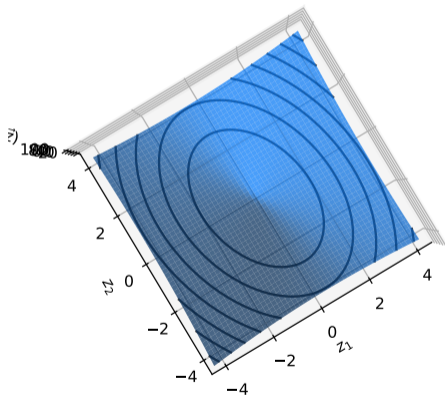
Contours



Contours

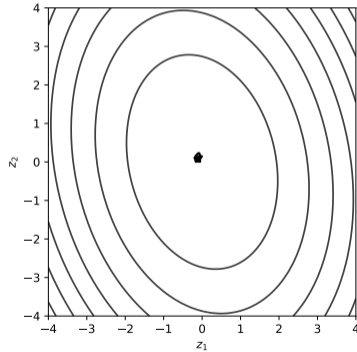
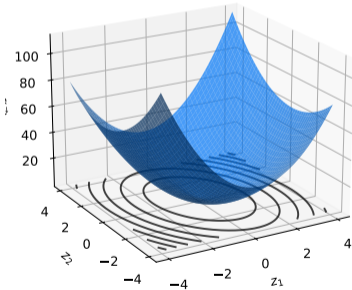


Contours



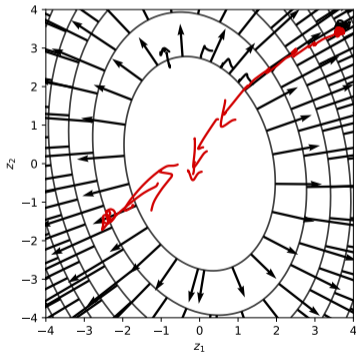
Contours

- ▶ The contours are the **level sets** of the function.



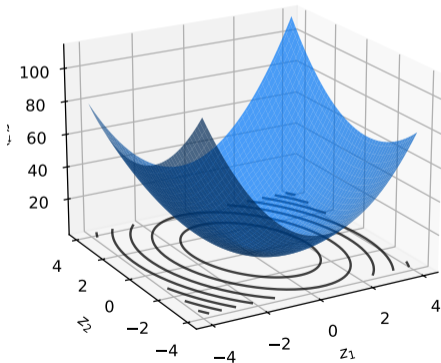
Contours and Gradients

- ▶ The gradient is **orthogonal** to the contours.



Optimization

- ▶ To find a **minimum** (or **maximum**), look for where the gradient is $\vec{0}$.



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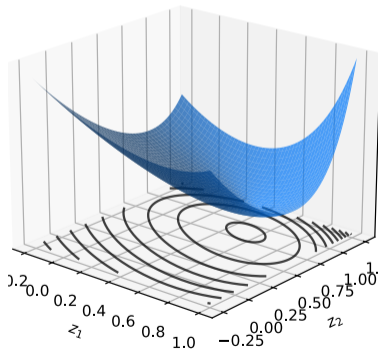
Probabilistic Modeling & Machine Learning

Lecture 3 | Part 3

Gradient Descent

Example

- **Goal:** minimize $f(\vec{z}) = e^{z_1^2+z_2^2} + (z_1 - 2)^2 + (z_2 - 3)^2$.



Example

- ▶ Try solving $\frac{df}{d\vec{z}}(\vec{z}) = 0$.

- ▶ The gradient is:

$$\frac{df}{d\vec{z}}(\vec{z}) = \begin{pmatrix} 2z_1 e^{z_1^2+z_2^2} + 2(z_1 - 2) \\ 2z_2 e^{z_1^2+z_2^2} + 2(z_2 - 3) \end{pmatrix}$$

- ▶ Can we solve the system?

$$2z_1 e^{z_1^2+z_2^2} + 2(z_1 - 2) = 0$$

$$2z_2 e^{z_1^2+z_2^2} + 2(z_2 - 3) = 0$$

Example

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- ▶ Can we solve the system? **Not in closed form.**

$$2z_1 e^{z_1^2+z_2^2} + 2(z_1 - 2) = 0$$

$$2z_2 e^{z_1^2+z_2^2} + 2(z_2 - 3) = 0$$

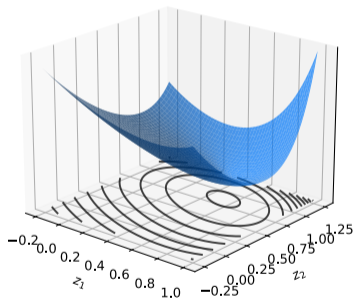
A Problem

- ▶ The function **is differentiable**².
- ▶ But we can't set gradient to zero and solve.
- ▶ **How do we find the minimum?**

²The gradient exists everywhere.

A Solution

- ▶ **Idea:** iterate towards a minimum, step by step.
- ▶ Start at an arbitrary location.
- ▶ At every step, move in direction of **steepest descent**.
 - ▶ i.e., the negative gradient.



Exercise

The gradient of a function $f(\vec{z})$ at $(1, 1)$ is $(2, 1)^T$.

If you're trying to minimize $f(\vec{z})$, which place should you go to next?

- ▶ A) $(1, 1)$
- ▶ B) $(.8, .9)$
- ▶ C) $(1.2, 1.1)$

Direction of Steepest Descent

- If η is the **learning rate**, then the next step is:

$$\vec{z}^{(t+1)} = \vec{z}^{(t)} - \underbrace{\eta}_{\text{"eta"}} \times \frac{df}{d\vec{z}}(\vec{z}^{(t)})$$

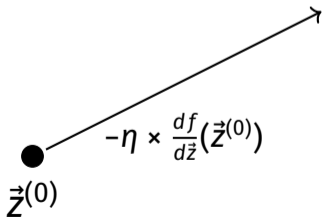
Handwritten annotations: "Step size" with an arrow pointing to the learning rate symbol, and wavy lines underlining the terms $\vec{z}^{(t)}$, η , and $\frac{df}{d\vec{z}}(\vec{z}^{(t)})$.

●
 $\vec{z}^{(0)}$

Direction of Steepest Descent

- ▶ If η is the **learning rate**, then the next step is:

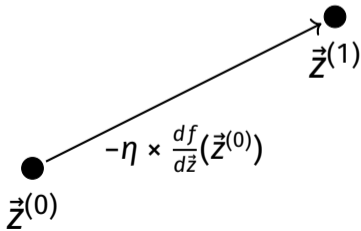
$$\vec{z}^{(t+1)} = \vec{z}^{(t)} - \eta \times \frac{df}{d\vec{z}}(\vec{z}^{(t)})$$



Direction of Steepest Descent

- ▶ If η is the **learning rate**, then the next step is:

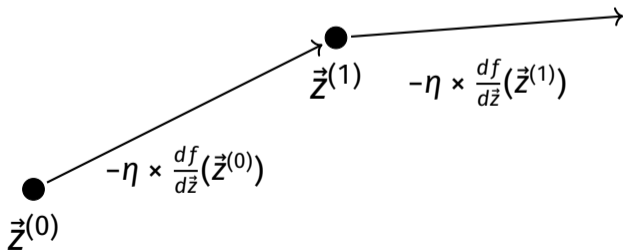
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Direction of Steepest Descent

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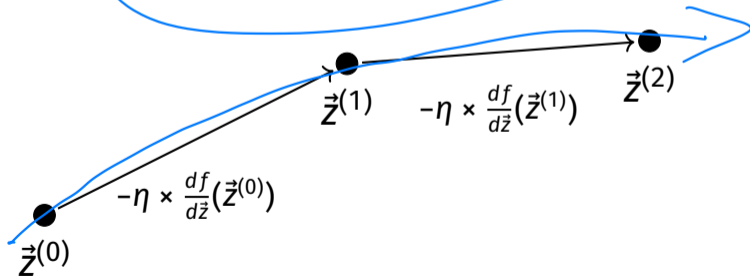
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Direction of Steepest Descent

- ▶ If η is the **learning rate**, then the next step is:

$$\vec{z}^{(t+1)} = \vec{z}^{(t)} - \eta \times \frac{df}{d\vec{z}}(\vec{z}^{(t)})$$



Gradient Descent

To minimize $f(\vec{z})$:

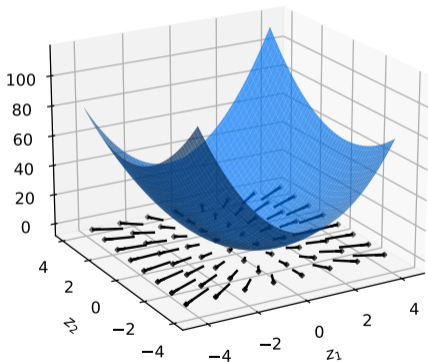
- ▶ Pick arbitrary starting point $\vec{z}^{(0)}$, **learning rate** $\eta > 0$
- ▶ Until convergence, repeat:
 - ▶ **Compute gradient:** $\frac{df}{d\vec{z}}(\vec{z}^{(t)})$ at $\vec{z}^{(t)}$.
 - ▶ **Update:** $\vec{z}^{(t+1)} = \vec{z}^{(t)} - \eta \times \frac{df}{d\vec{z}}(\vec{z}^{(t)})$.
- ▶ When converged, return $\vec{z}^{(t)}$.
- ▶ It is (approximately) a local minimum.

= we're done

while loop

$$\|\vec{z}^{(t+1)} - \vec{z}^{(t)}\| = \eta \left\| \frac{df}{d\vec{z}} \right\| = \eta \left\| \frac{df}{d\vec{z}} \right\|$$

Stopping Criterion



gradient norm

- ▶ Close to a minimum, gradient is small.

▶ **Idea:** stop when $\left\| \frac{df}{d\vec{z}}(\vec{z}^{(t)}) \right\|$ is small.

- ▶ **Alternative:** stop when $\left\| \vec{z}^{(t+1)} - \vec{z}^{(t)} \right\|$ is small.

```
def gradient_descent(
    gradient, z_0, learning_rate, stop_threshold
):
    z = z_0
    while True:
        z_new = z - learning_rate * gradient(z)
        if np.linalg.norm(z_new - z) < stop_threshold:
            break
        z = z_new
    return z_new
```

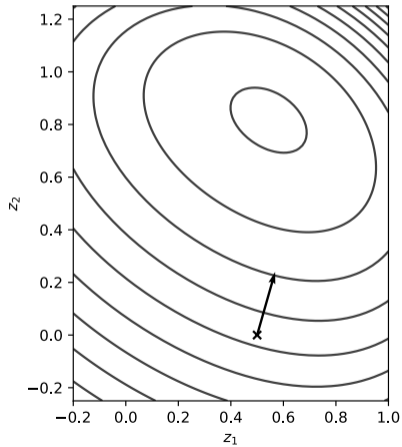
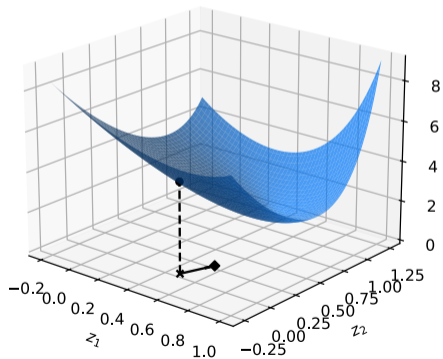
Handwritten annotations:

- initial point* (with arrow pointing to `z_0`)
- check convergence* (with arrow pointing to the `if` statement)

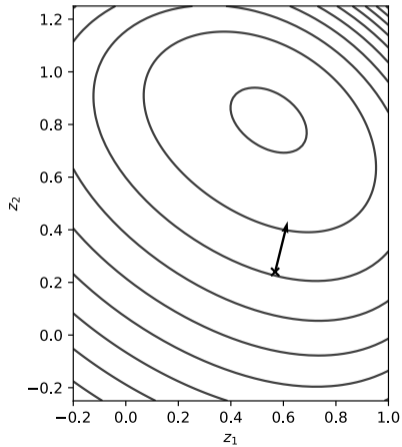
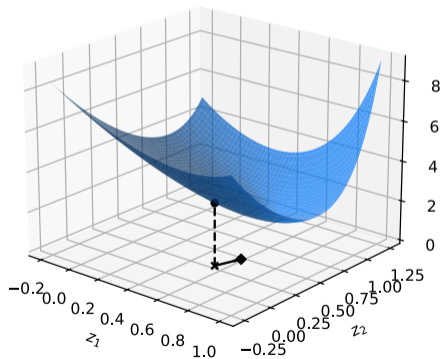
Picking Parameters

- ▶ The learning rate and stopping threshold are **parameters**.
- ▶ They need to be chosen carefully for each problem.
- ▶ If not, the algorithm **may not converge**.

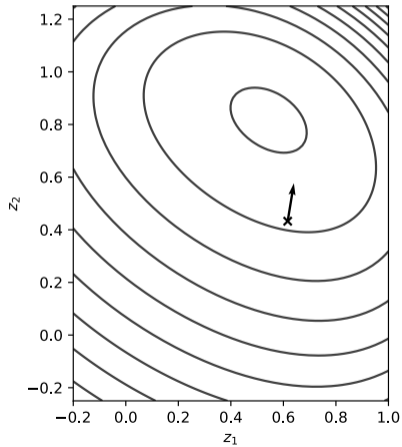
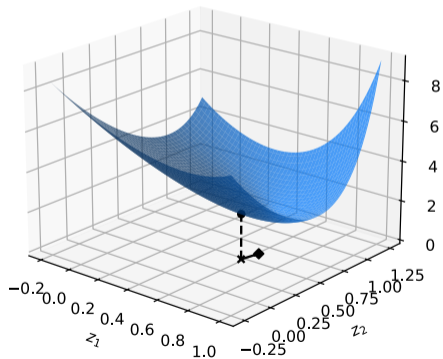
Example



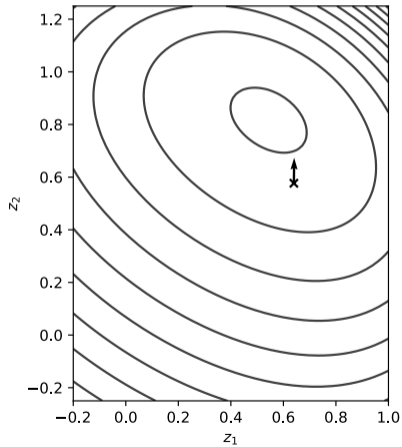
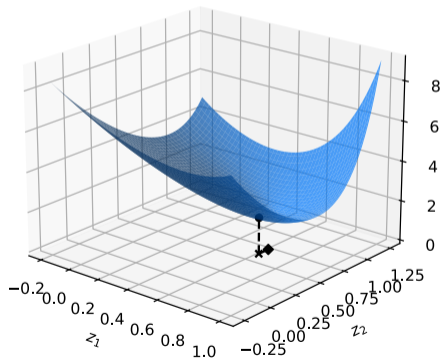
Example



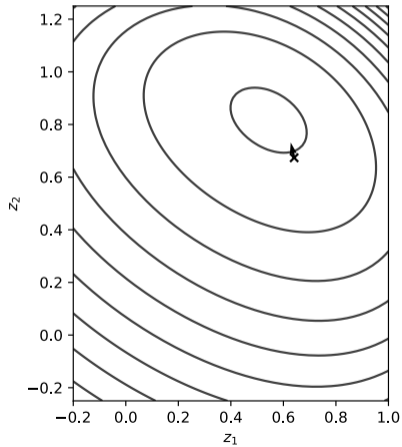
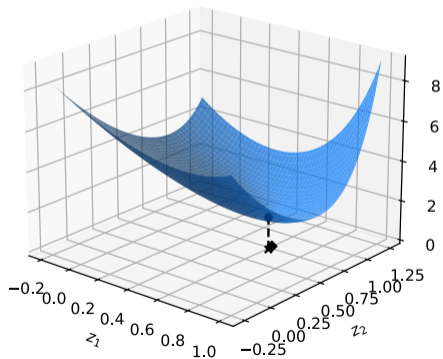
Example



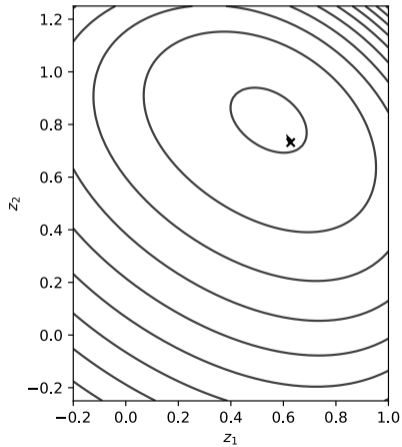
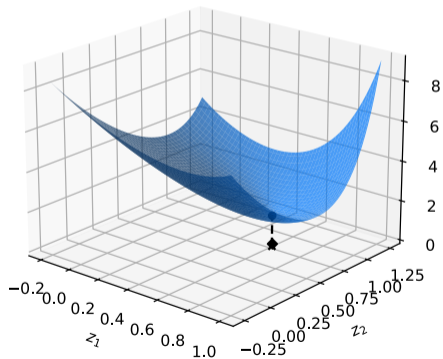
Example



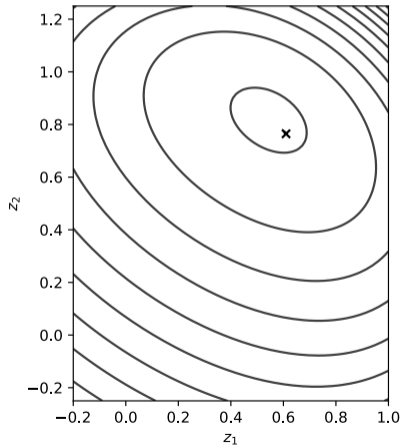
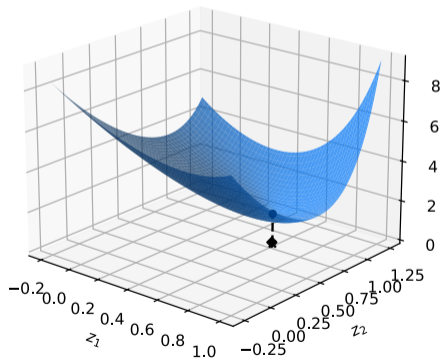
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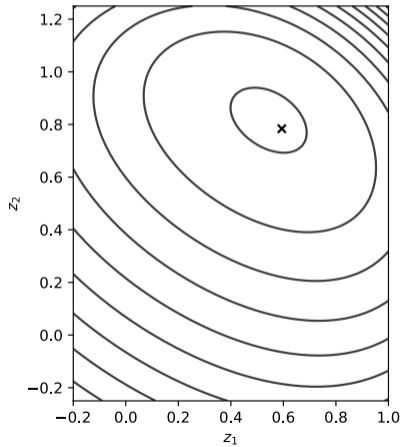
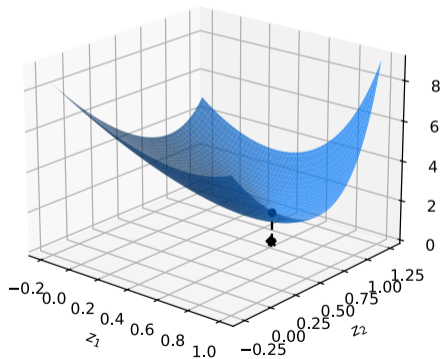
Example



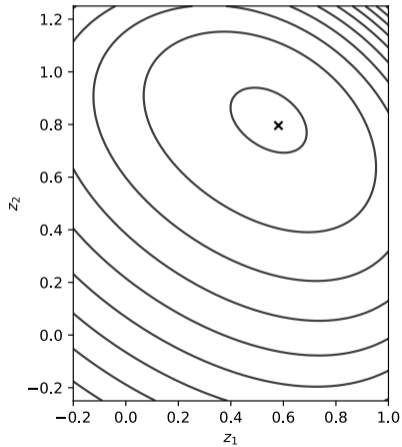
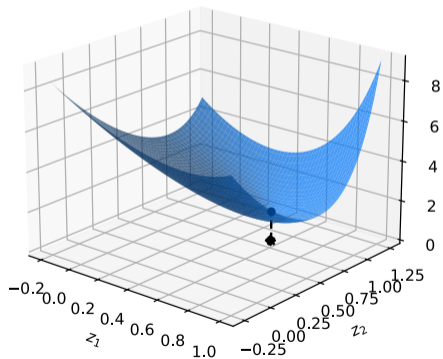
Example



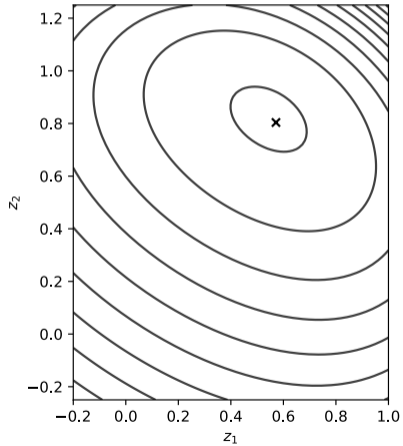
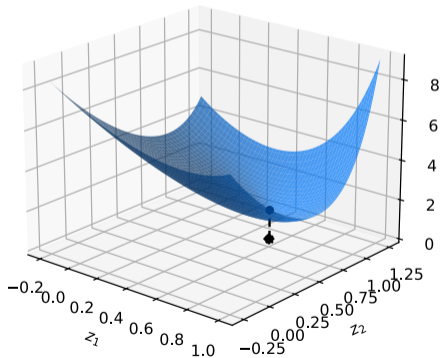
Example



Example



Example



$$\frac{df}{dz} = \begin{pmatrix} 4z_1 + z_2 \\ 6z_2 + z_1 \end{pmatrix} \Rightarrow \frac{df}{dz}(1,1) = \begin{pmatrix} 5 \\ 7 \end{pmatrix}$$

Exercise

Let $f(z_1, z_2) = z_1^4 + 3z_2^2 + z_1z_2$.

Starting at $\vec{z}^{(0)} = (1, 1)$, what is the next point after one step of gradient descent with learning rate $\eta = 0.1$?

$$\begin{aligned} \underline{z}^{(1)} &= \underline{z}^{(0)} - \eta \frac{df}{dz}(\underline{z}^{(0)}) \\ &= \begin{pmatrix} 1 \\ 1 \end{pmatrix} - (0.1) \begin{pmatrix} 5 \\ 7 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \end{pmatrix} - \begin{pmatrix} .5 \\ .7 \end{pmatrix} = \begin{pmatrix} .5 \\ .3 \end{pmatrix} \end{aligned}$$

DSC 140A

Probabilistic Modeling & Machine Learning

Lecture 3 | Part 4

Gradient Descent for ERM

Gradient Descent for ERM

- ▶ In ERM, our goal is to minimize **empirical risk**:³

$$R(\vec{w}) = \frac{1}{n} \sum_{i=1}^n \ell(\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w}, y_i)$$

- ▶ Often, we can minimize using **gradient descent**.

³We've assumed H is a linear prediction function.

The Gradient of the Risk

- ▶ The gradient of the empirical risk is:

$$\begin{aligned}\frac{dR}{d\vec{w}}(\vec{w}) &= \frac{d}{d\vec{w}} \left(\frac{1}{n} \sum_{i=1}^n \ell(\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w}, y_i) \right) \\ &= \frac{1}{n} \sum_{i=1}^n \frac{d\ell}{d\vec{w}}(\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w}, y_i)\end{aligned}$$

- ▶ Gradient of risk is average gradient of loss.
- ▶ As far as we can go without knowing the loss.

The Gradient of the MSE

- ▶ Recall: the **mean squared error** is the empirical risk with respect to the square loss:

$$R(\vec{w}) = \frac{1}{n} \sum_{i=1}^n (\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w} - y_i)^2$$

- ▶ The gradient is: *average gradient of loss*

$$\frac{dR}{d\vec{w}}(\vec{w}) = \frac{1}{n} \sum_{i=1}^n \frac{d}{d\vec{w}} (\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w} - y_i)^2$$

Exercise

Recall that the square loss for a linear predictor is:
 $(\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w} - y_i)^2$.

What is the gradient of the square loss with respect to \vec{w} ?

$$\begin{aligned} \frac{d}{d\vec{w}} (\vec{x}^{(i)} \cdot \vec{w} - y_i)^2 &\approx 2 (\vec{x}^{(i)} \cdot \vec{w} - y_i) \frac{d}{d\vec{w}} (\vec{x}^{(i)} \cdot \vec{w} - y_i) \\ &\approx 2 \underbrace{(\vec{x}^{(i)} \cdot \vec{w} - y_i)}_{\text{Scalar}} \underbrace{\vec{x}^{(i)}}_{\text{vector}} \end{aligned}$$

“residual”
“error”

The Gradient of the MSE

- ▶ The gradient of the mean squared error is:⁴

$$\frac{dR}{d\vec{w}}(\vec{w}) = \frac{2}{n} \sum_{i=1}^n (\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w} - y_i) \text{Aug}(\vec{x}^{(i)})$$

- ▶ Each training point $\vec{x}^{(i)}$ contributes to the gradient.

A handwritten diagram in blue and red ink. It shows the expression $2X^T(X\vec{w} - \vec{y})$ circled in red. A red arrow points from the text "vector of residuals" to the term $(X\vec{w} - \vec{y})$. A blue arrow points from the term $2X^T$ to the left. A blue bracket is drawn under the entire expression $2X^T(X\vec{w} - \vec{y})$.

⁴We saw before that $\frac{dR}{d\vec{w}}(\vec{w}) = 2X^T X \vec{w} - 2X^T \vec{y}$. These two are actually equal.

Exercise

What will be the gradient if every prediction is exactly correct?

$$\frac{dR}{d\vec{w}}(\vec{w}) = \frac{2}{n} \sum_{i=1}^n (\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w} - y_i) \text{Aug}(\vec{x}^{(i)})$$

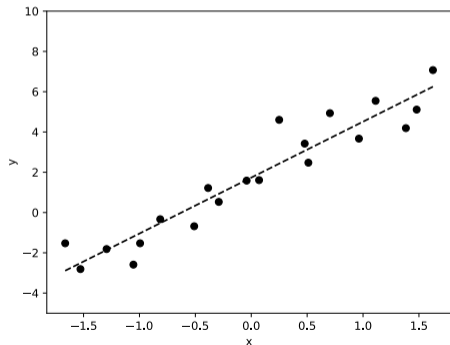
Gradient Descent for Least Squares

- ▶ We can perform least squares regression by solving the normal equations: $\vec{w}^* = (X^T X)^{-1} X^T \vec{y}$.
- ▶ But we can find the **same solution** using **gradient descent**:

$$\vec{w}^{(t+1)} = \vec{w}^{(t)} - \eta \times \frac{2}{n} \sum_{i=1}^n (\text{Aug}(\vec{x}^{(i)}) \cdot \vec{w}^{(t)} - y_i) \text{Aug}(\vec{x}^{(i)})$$

Example

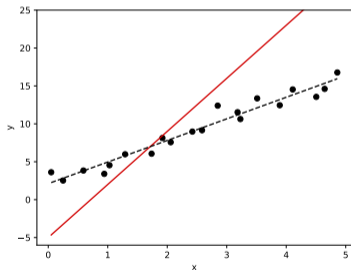
- ▶ We will run gradient descent to train a least squares regression model on the following data:



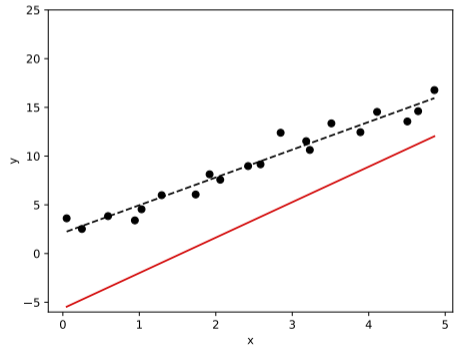
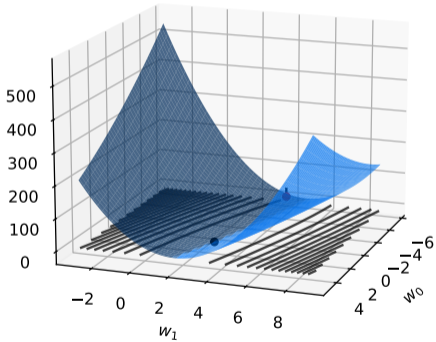
Exercise

The plot below shows a linear prediction function using weight vector $\vec{w}^{(0)}$.

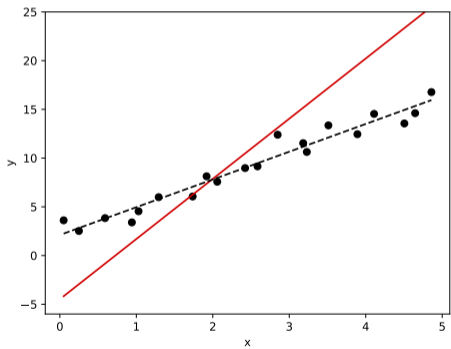
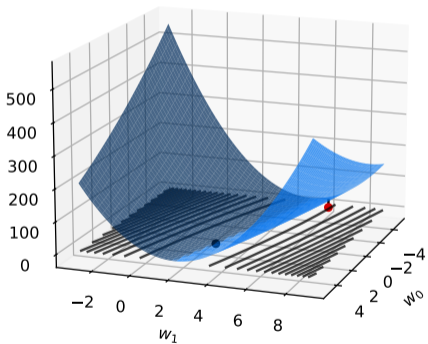
What is the sign of the **second** entry of $\frac{dR}{d\vec{w}}(\vec{w}^{(0)})$?



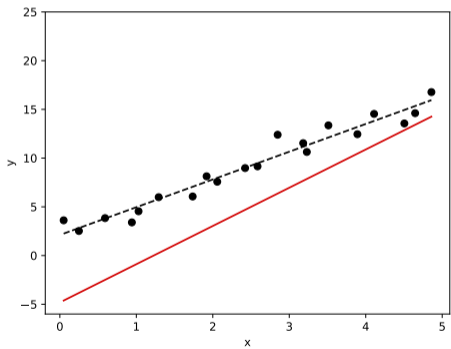
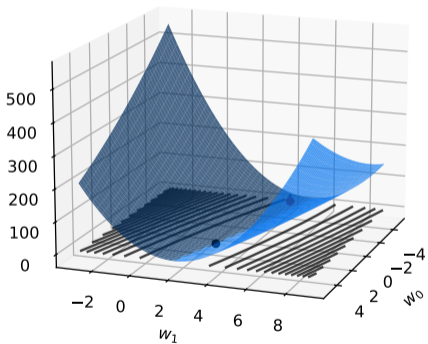
Iteration #1



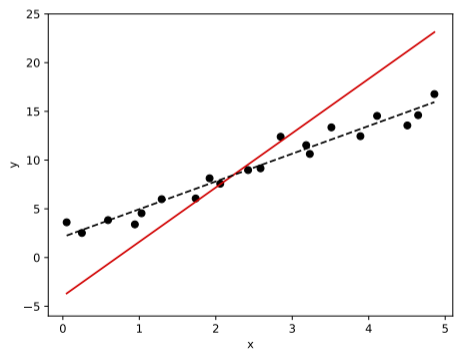
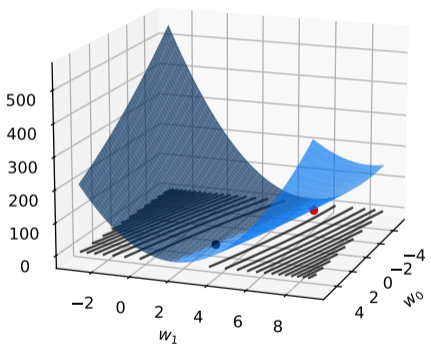
Iteration #2



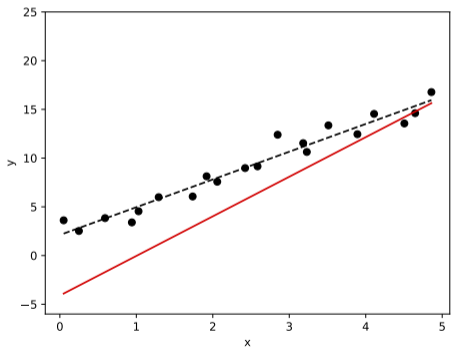
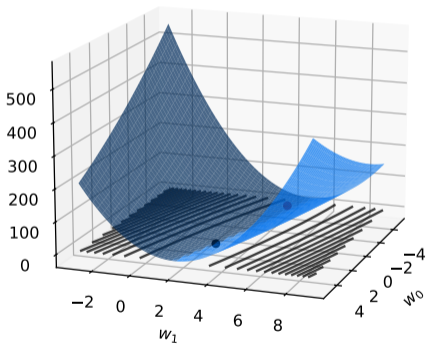
Iteration #3



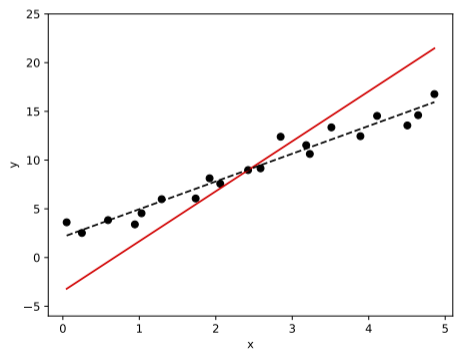
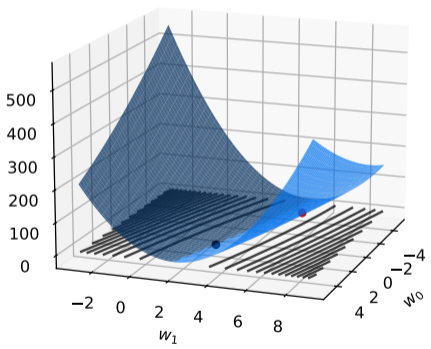
Iteration #4



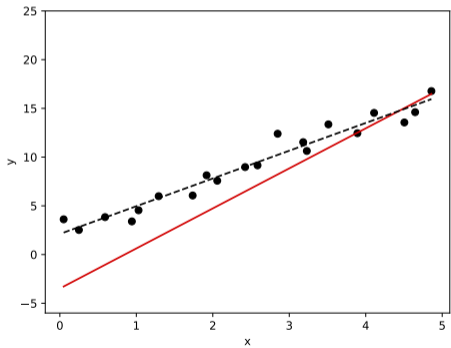
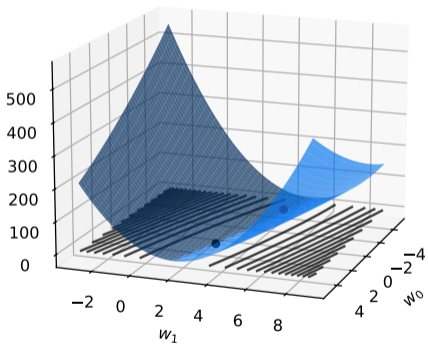
Iteration #5



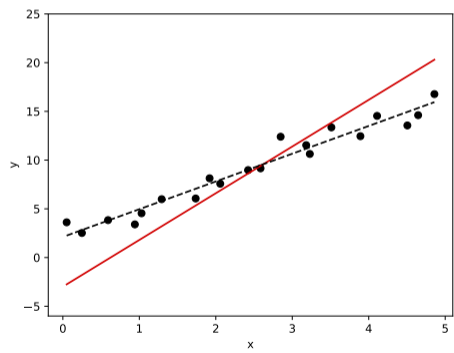
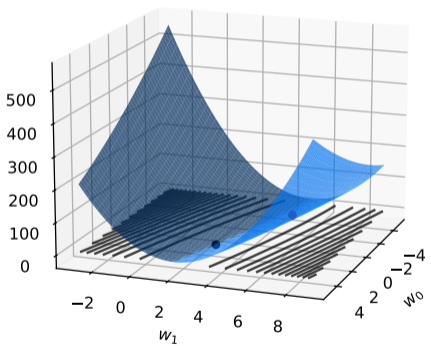
Iteration #6



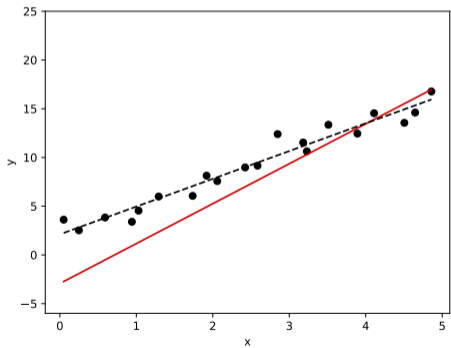
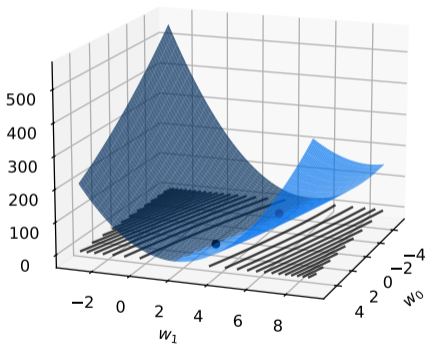
Iteration #7



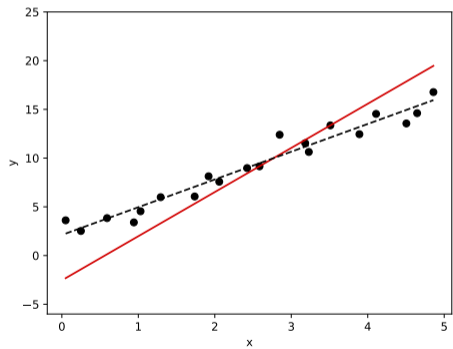
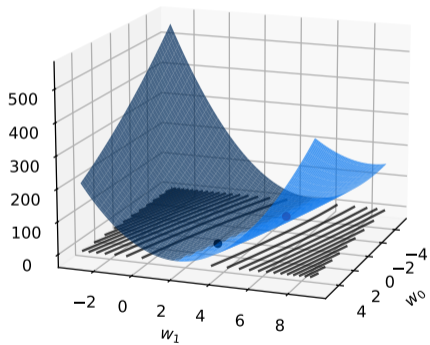
Iteration #8



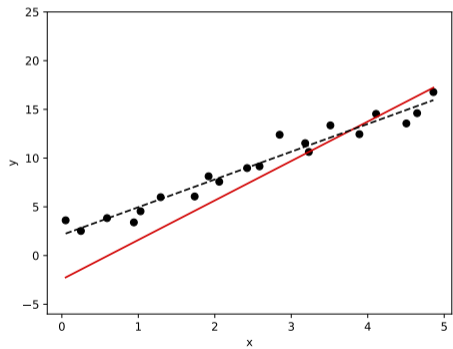
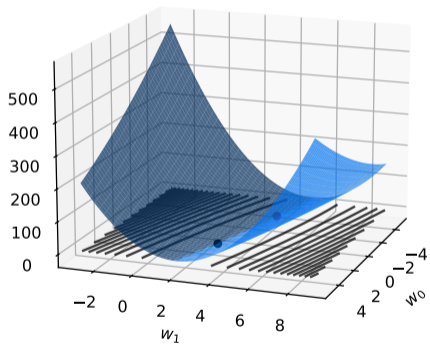
Iteration #9



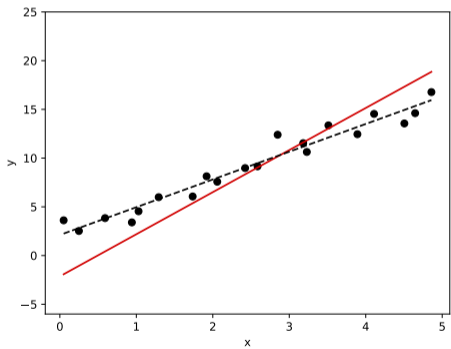
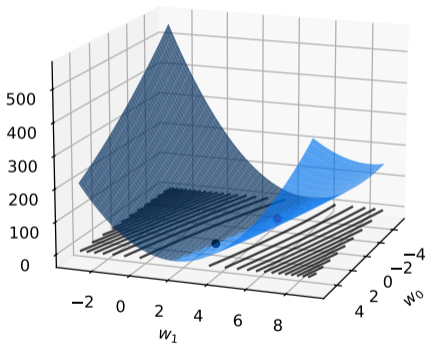
Iteration #10



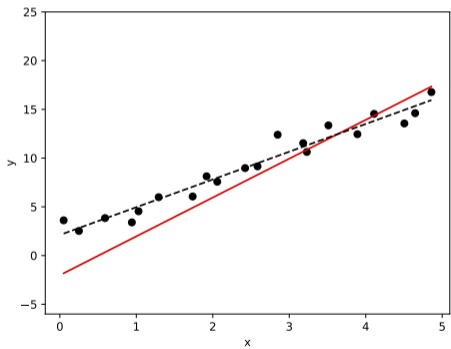
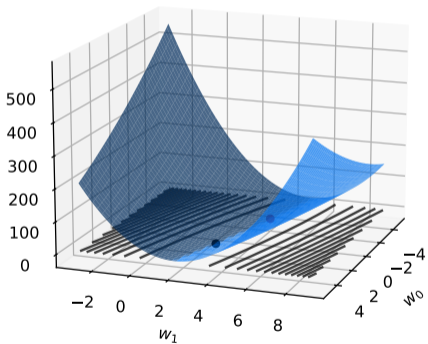
Iteration #11



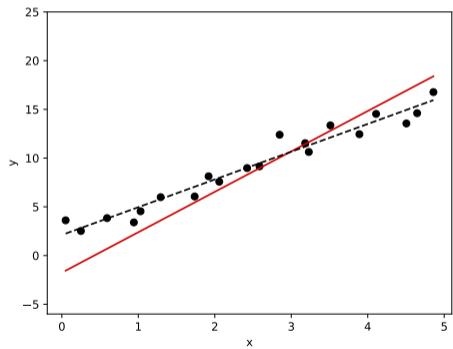
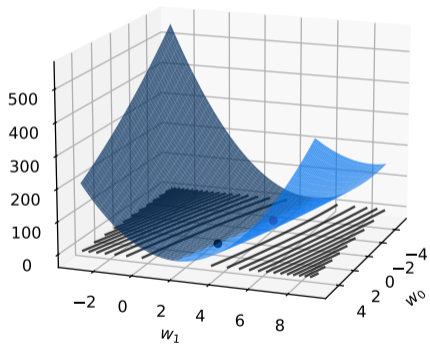
Iteration #12



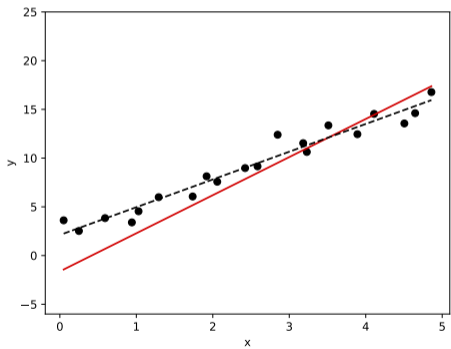
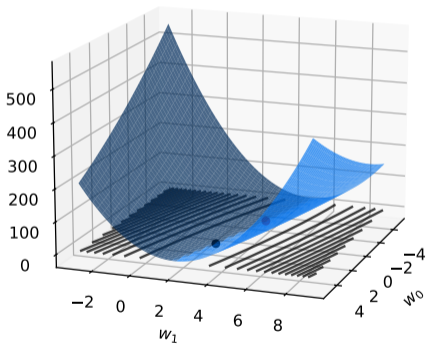
Iteration #13



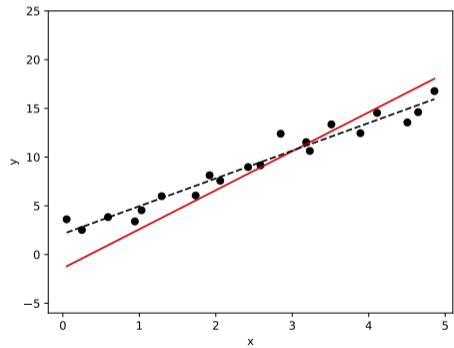
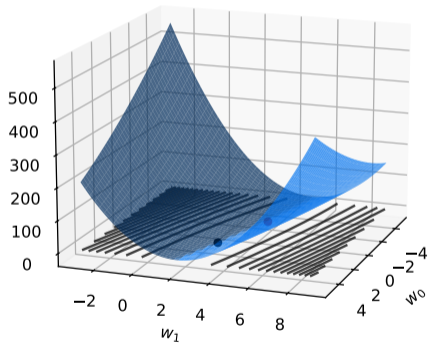
Iteration #14



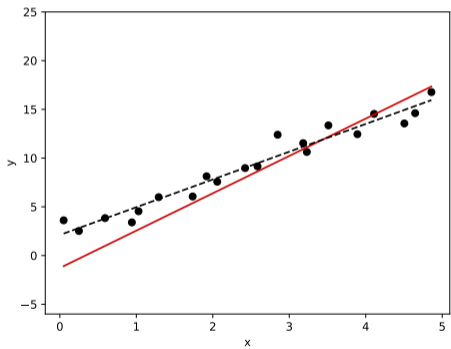
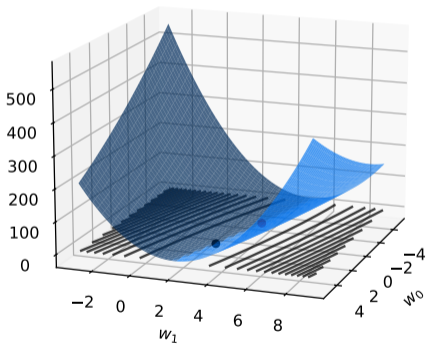
Iteration #15



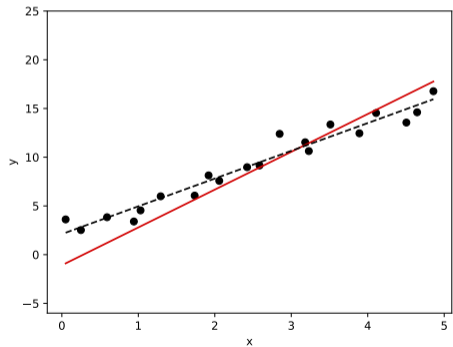
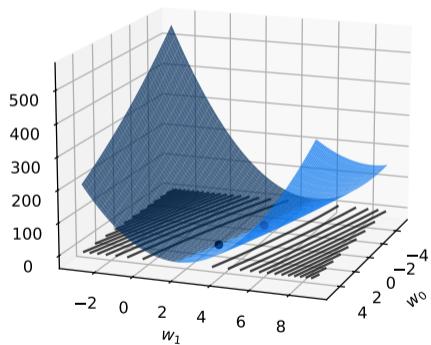
Iteration #16



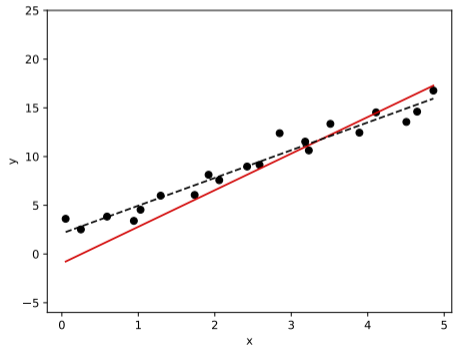
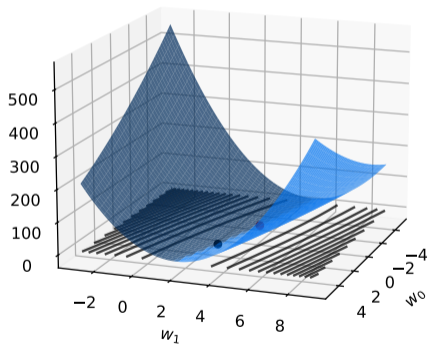
Iteration #17



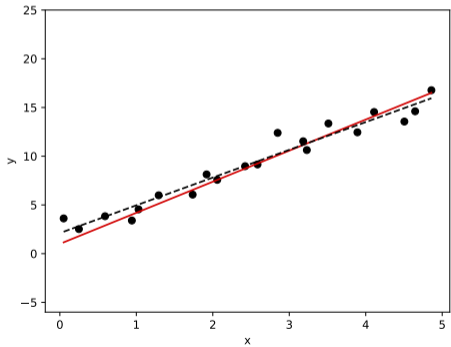
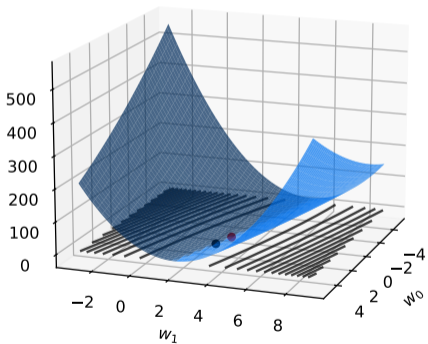
Iteration #18



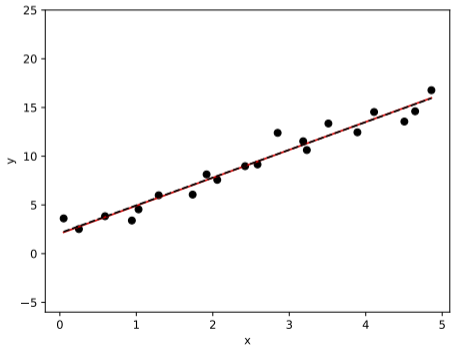
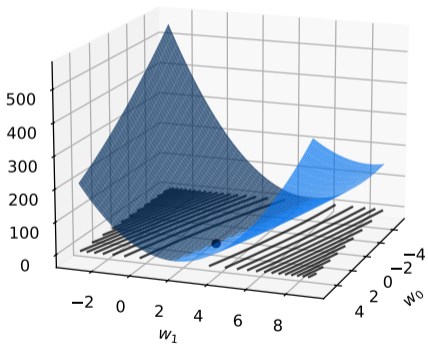
Iteration #19



Iteration #40



Iteration #100



DSC 140A

Probabilistic Modeling & Machine Learning

Lecture 3 | Part 5

Appendix: From Theory to Practice

In Practice

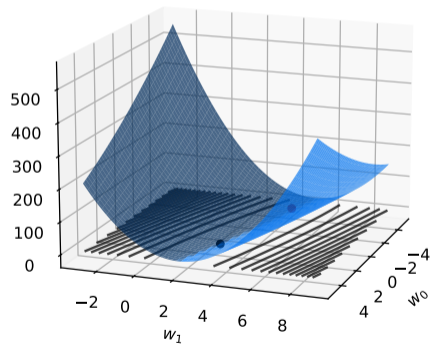
- ▶ (S)GD is **heavily used** in machine learning.
- ▶ Can be used to solve many optimization problems.
- ▶ But it can be tricky to get working.

Learning Rate

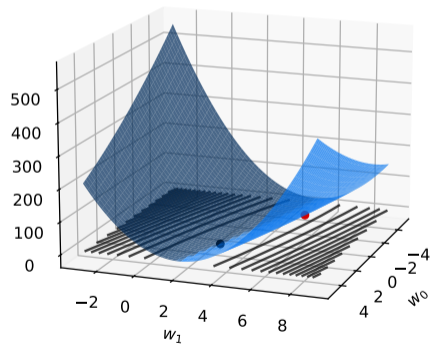
f initial value

- ▶ The learning rate has to be chosen carefully.
- ▶ If too large, the algorithm may **diverge**.
- ▶ If too small, the algorithm may **converge slowly**.

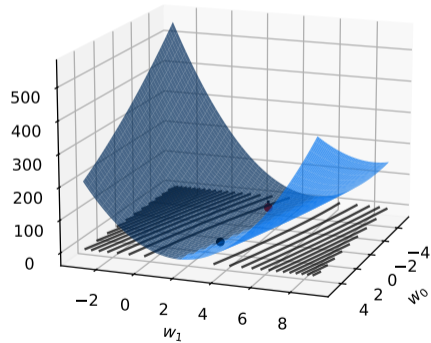
Diverging



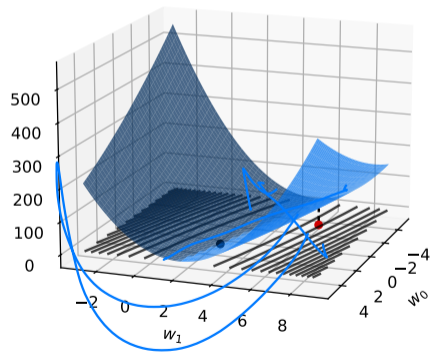
Diverging



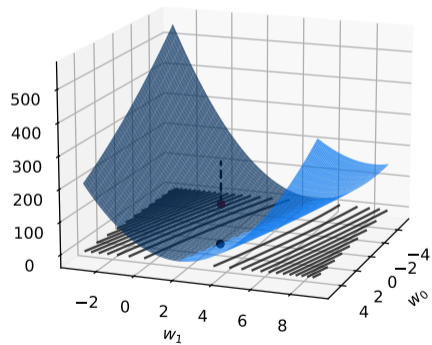
Diverging



Diverging



Diverging

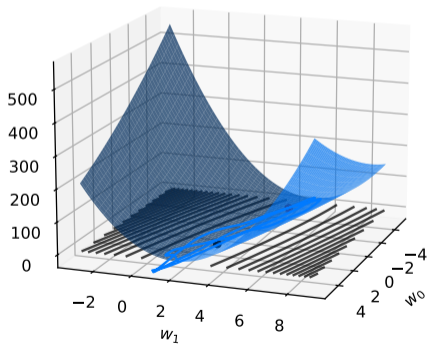


Diverging

- ▶ To diagnose, print $R(\vec{w})$ at each iteration.
- ▶ If it is increasing consistently, the algorithm is diverging.
- ▶ **Fix:** decrease the learning rate.
 - ▶ But not by too much! Then it may converge **too slowly**.

Problem

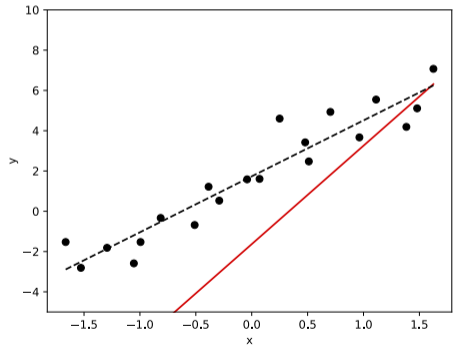
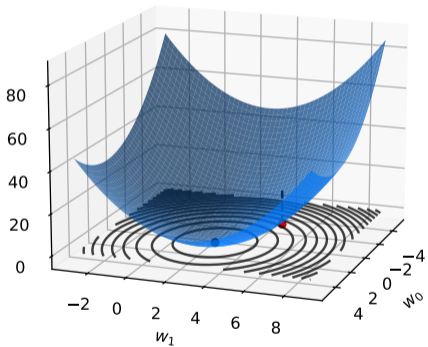
- ▶ When the contours are “long and skinny,” you will be forced to pick a very small learning rate.



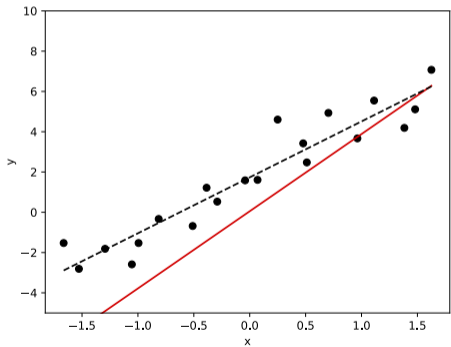
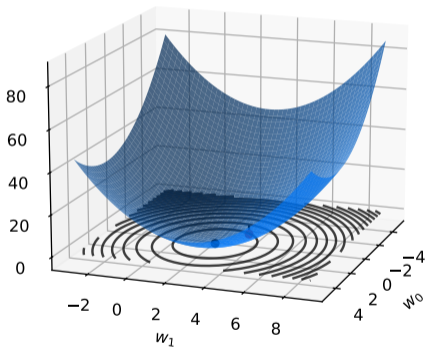
A Fix

- ▶ Scaling (standardizing) the features can help.
- ▶ This makes the contours more circular.
- ▶ Doesn't change the prediction!

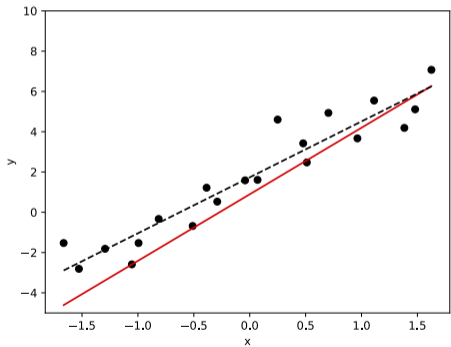
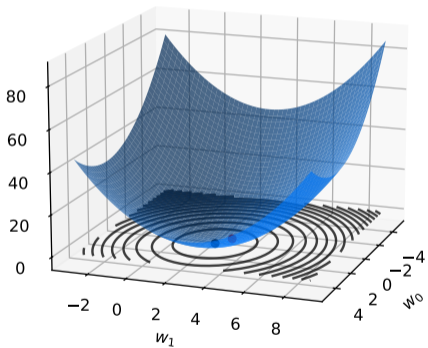
Iteration #1



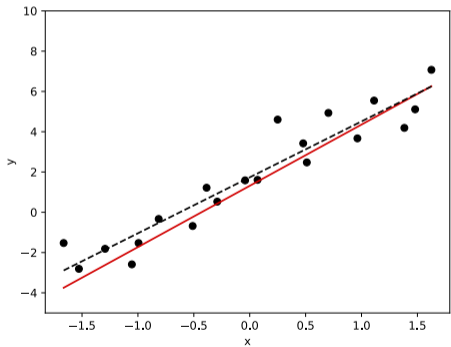
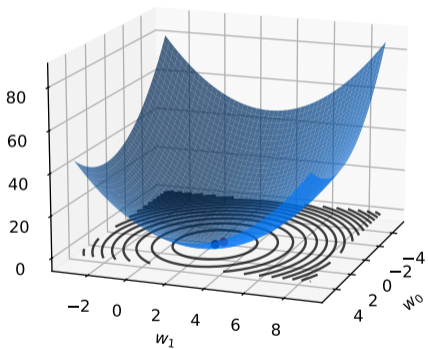
Iteration #2



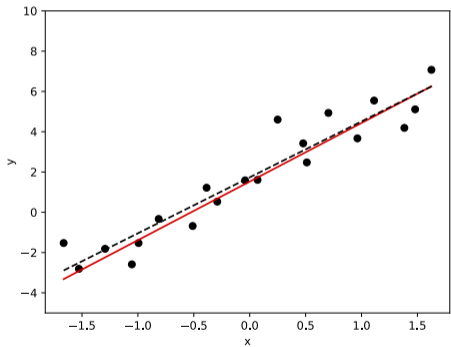
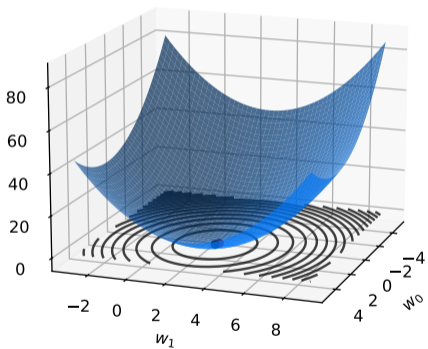
Iteration #3



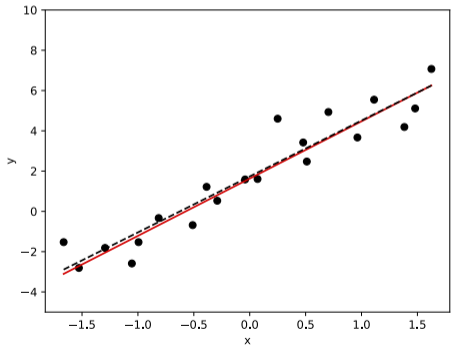
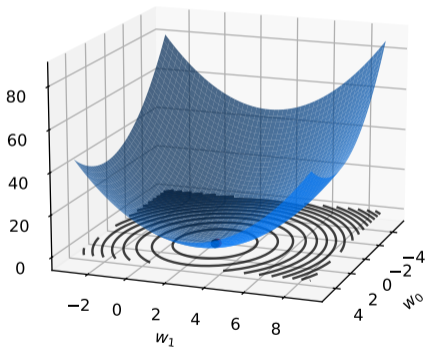
Iteration #4



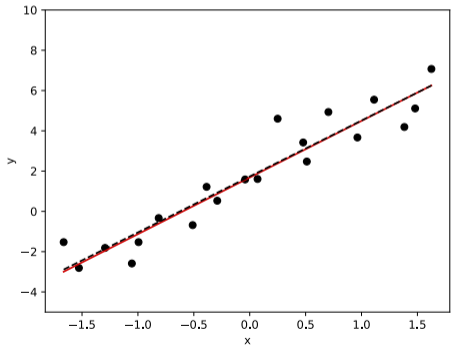
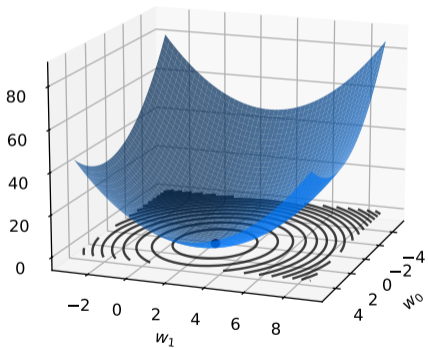
Iteration #5



Iteration #6



Iteration #7



Next Time

- ▶ How do we minimize the risk with respect to absolute loss?
- ▶ When is gradient descent guaranteed to converge?