

## EE-559 – Deep learning

### 3.5. Gradient descent

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<https://fleuret.org/ee559/>

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We saw that training consists of finding the model parameters minimizing an empirical risk or loss, for instance the mean-squared error (MSE)

$$\mathcal{L}(w, b) = \frac{1}{N} \sum_n (f(x_n; w, b) - y_n)^2.$$

Other losses are more fitting for classification, certain regression problems, or density estimation. We will come back to this.

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So far we minimized the loss either with an analytic solution for the MSE, or with *ad hoc* recipes for the empirical error rate (*k*-NN and perceptron).

There is generally no *ad hoc* method. The logistic regression for instance

$$P_w(Y = 1 | X = x) = \sigma(w \cdot x + b), \text{ with } \sigma(x) = \frac{1}{1 + e^{-x}}$$

leads to the loss

$$\mathcal{L}(w, b) = - \sum_n \log \sigma(y_n(w \cdot x_n + b))$$

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The general minimization method used in such a case is the **gradient descent**.

Given a functional

$$f : \mathbb{R}^D \rightarrow \mathbb{R}$$
$$x \mapsto f(x_1, \dots, x_D),$$

its gradient is the mapping

$$\nabla f : \mathbb{R}^D \rightarrow \mathbb{R}^D$$
$$x \mapsto \left( \frac{\partial f}{\partial x_1}(x), \dots, \frac{\partial f}{\partial x_D}(x) \right).$$

To minimize a functional

$$\mathcal{L} : \mathbb{R}^D \rightarrow \mathbb{R}$$

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For  $w_0 \in \mathbb{R}^D$ , consider an approximation of  $\mathcal{L}$  around  $w_0$

$$\tilde{\mathcal{L}}_{w_0}(w) = \mathcal{L}(w_0) + \nabla \mathcal{L}(w_0)^T (w - w_0) + \frac{1}{2\eta} \|w - w_0\|^2.$$

Note that the chosen quadratic term does not depend on  $\mathcal{L}$ .



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We have

$$\nabla \tilde{\mathcal{L}}_{w_0}(w) = \nabla \mathcal{L}(w_0) + \frac{1}{\eta} (w - w_0),$$

which leads to

$$\underset{w}{\operatorname{argmin}} \tilde{\mathcal{L}}_{w_0}(w) = w_0 - \eta \nabla \mathcal{L}(w_0).$$

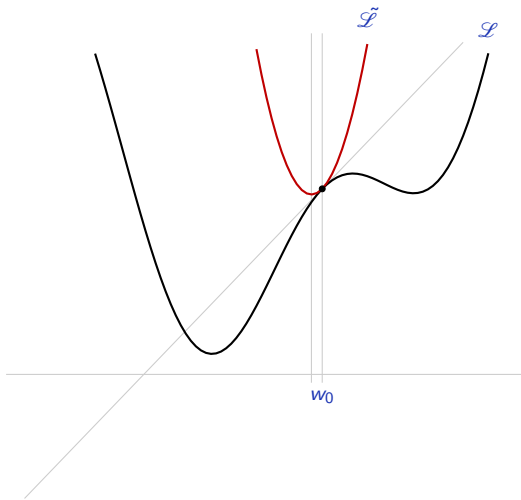
The resulting iterative rule, which goes to the minimum of the approximation at the current location, takes the form:

$$w_{t+1} = w_t - \eta \nabla \mathcal{L}(w_t),$$

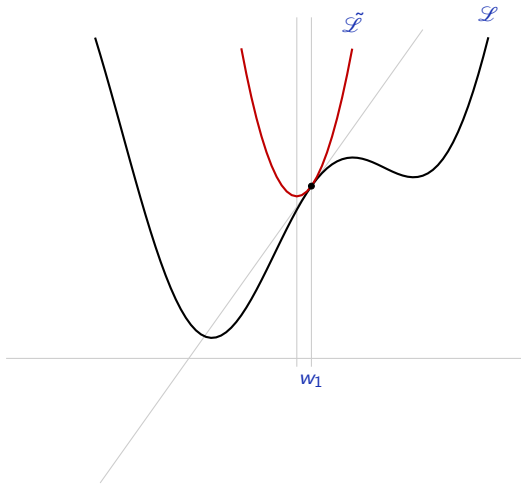
which corresponds intuitively to “following the steepest descent”.

This [most of the time] eventually ends up in a **local** minimum, and the choices of  $w_0$  and  $\eta$  are important.

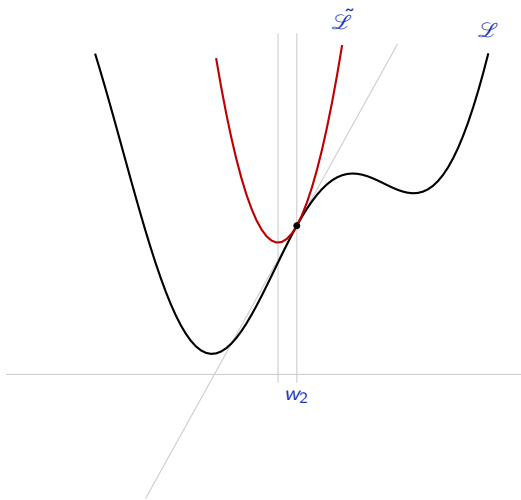
$$\eta = 0.125$$



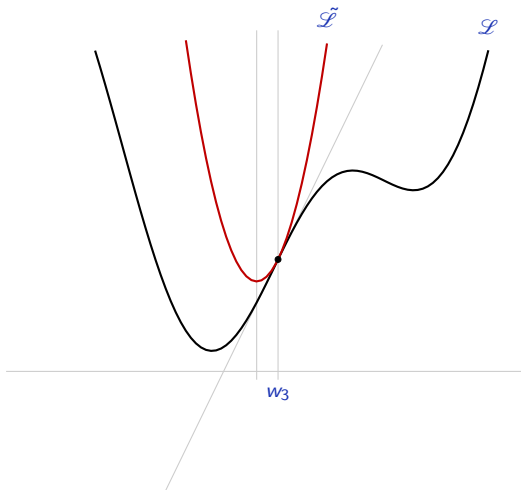
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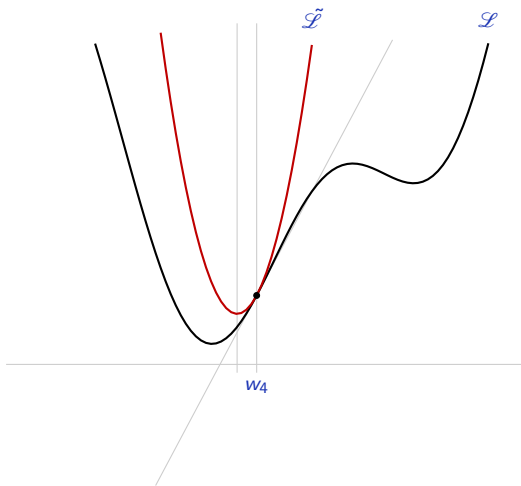
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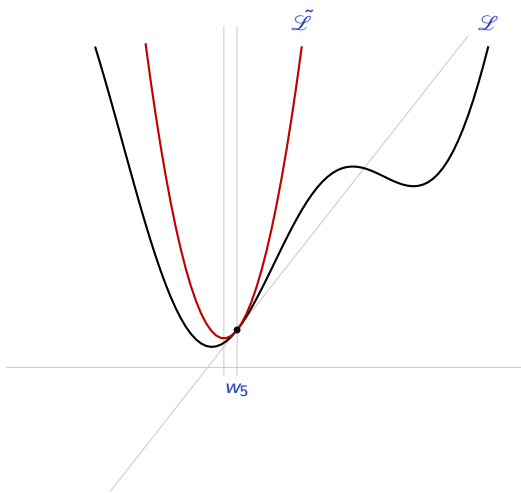
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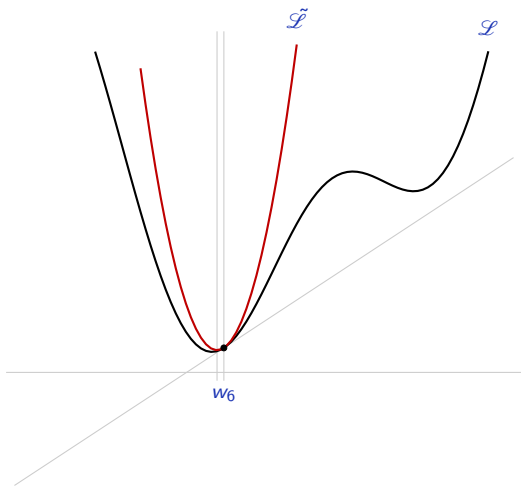


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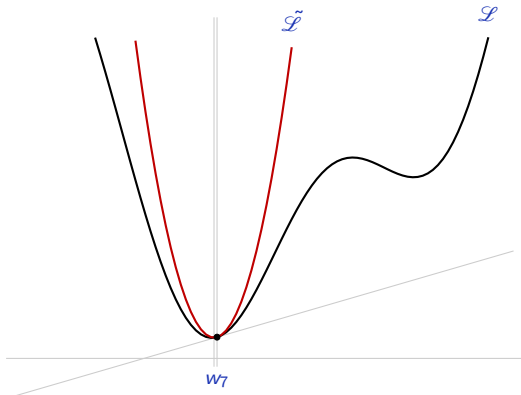




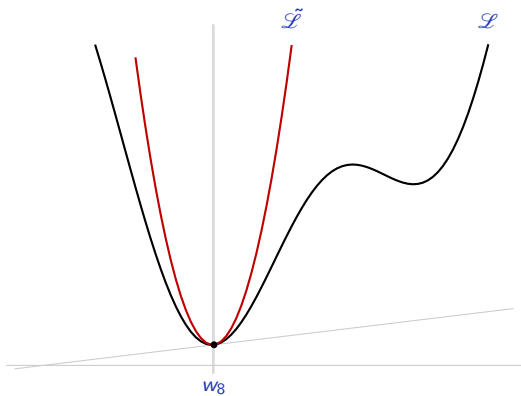
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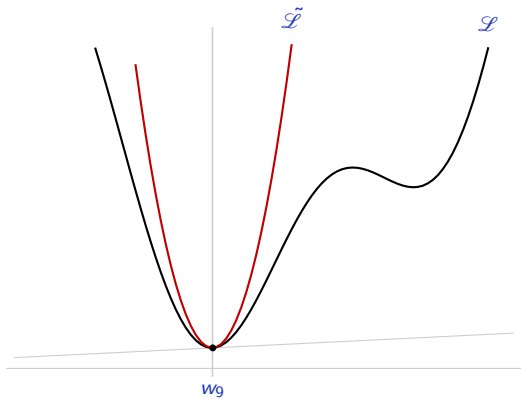
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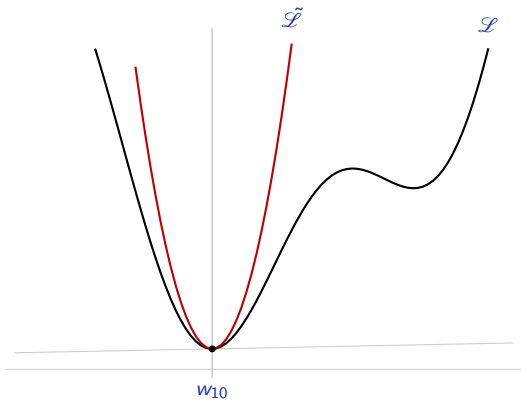
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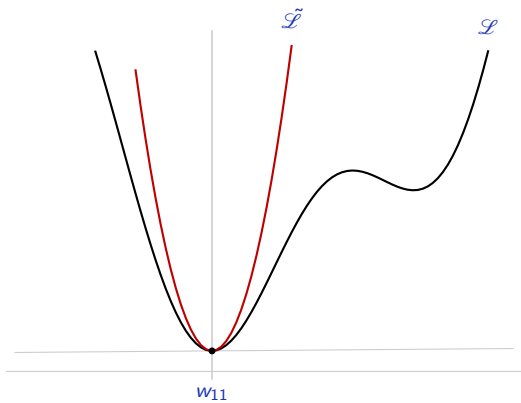
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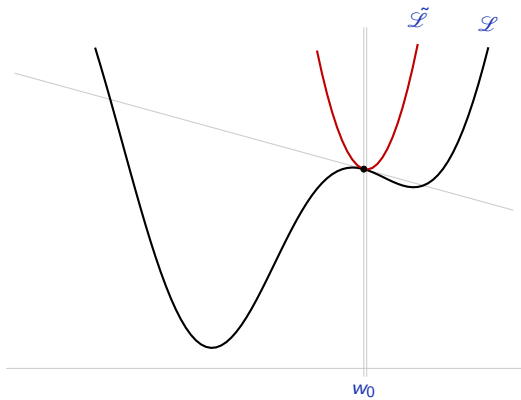
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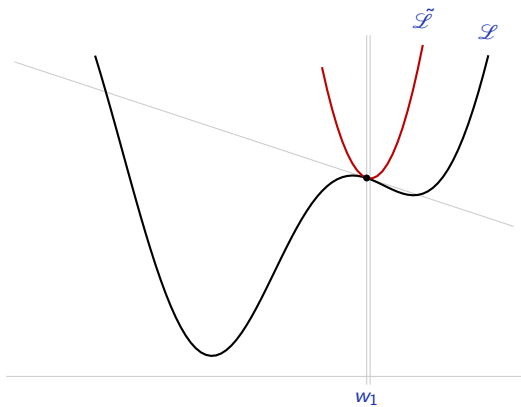
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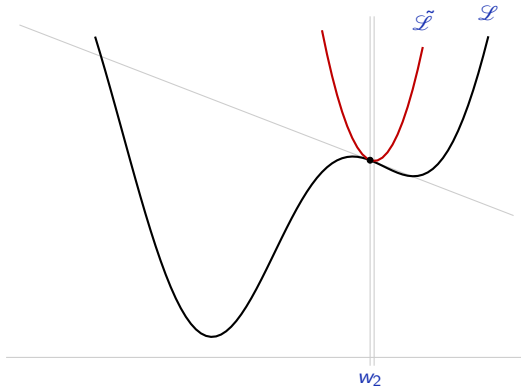


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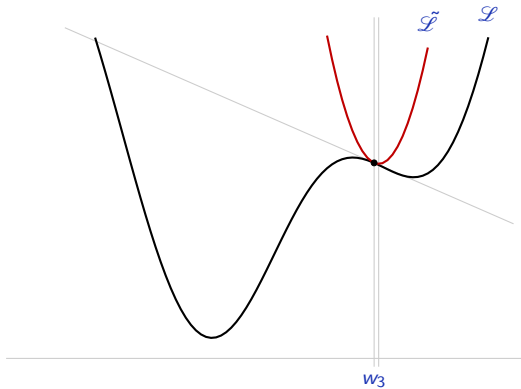




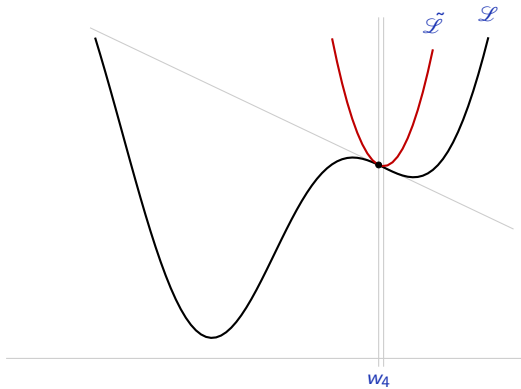
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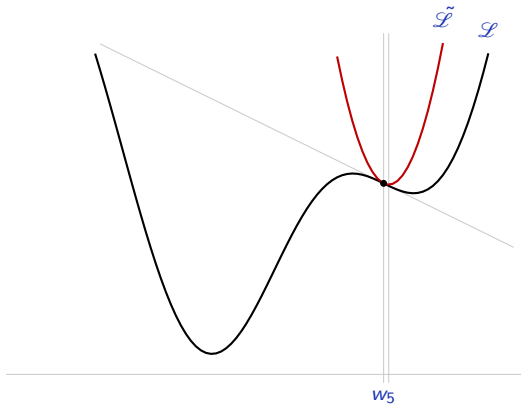
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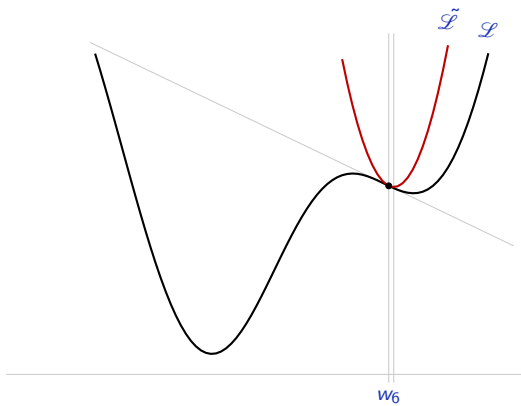
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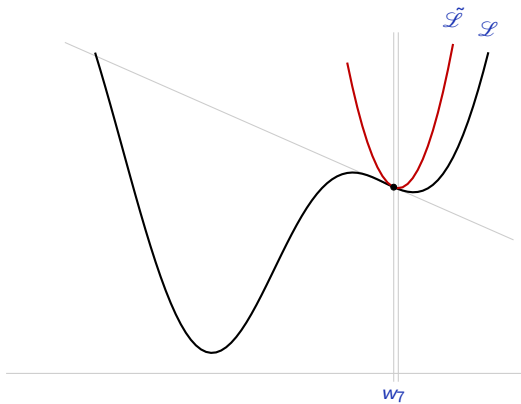
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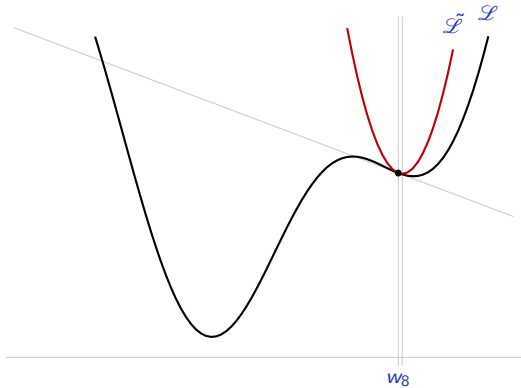
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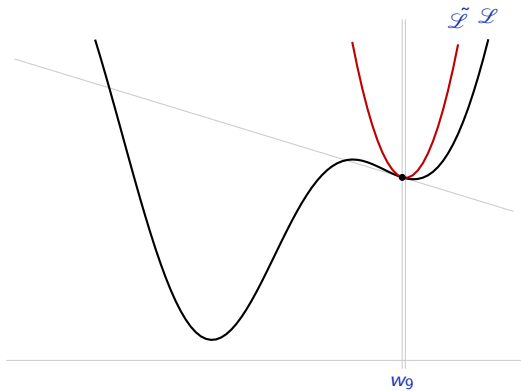
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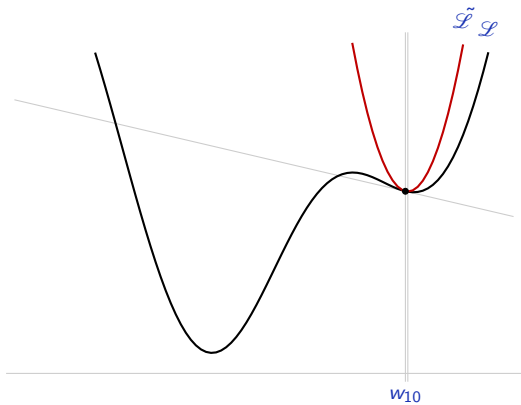


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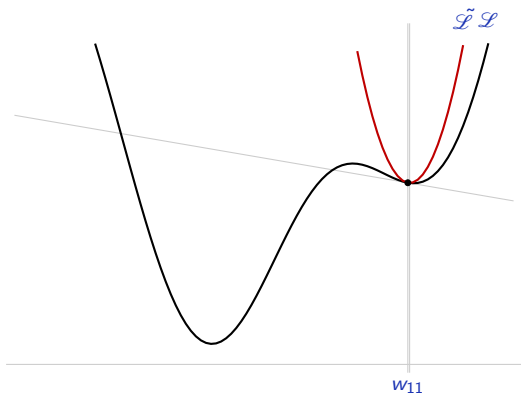




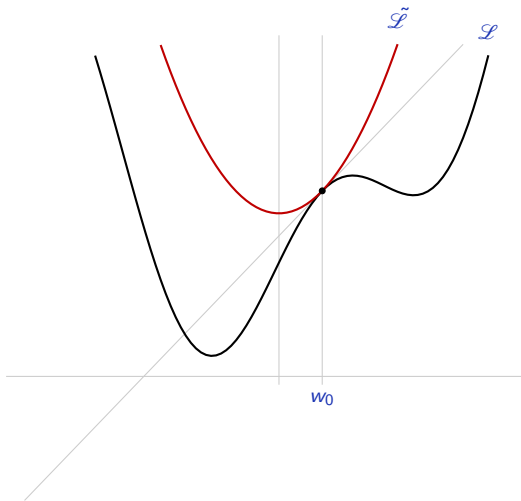
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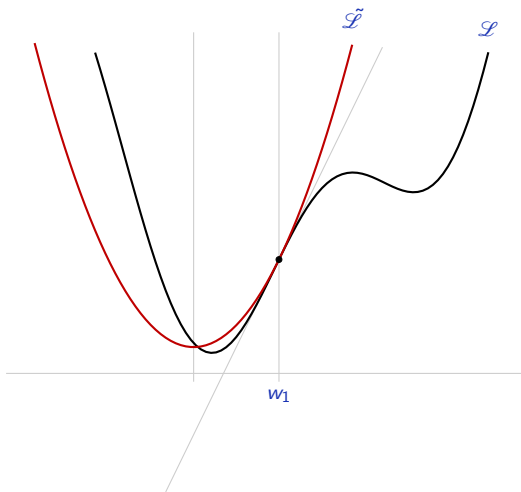
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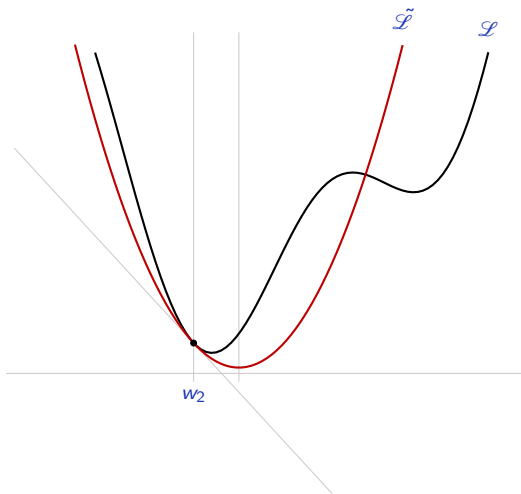
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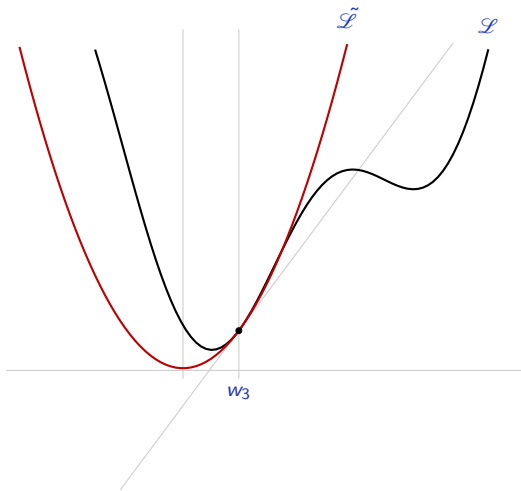
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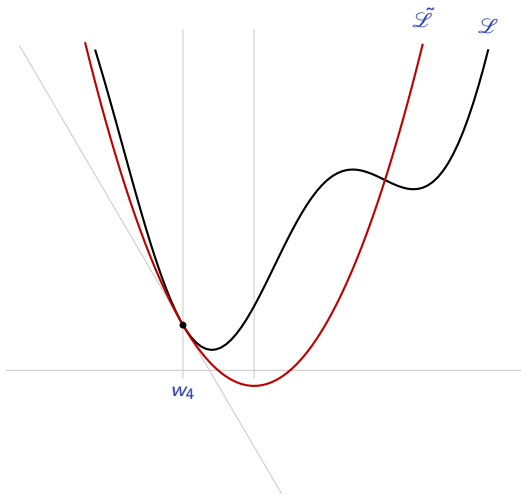
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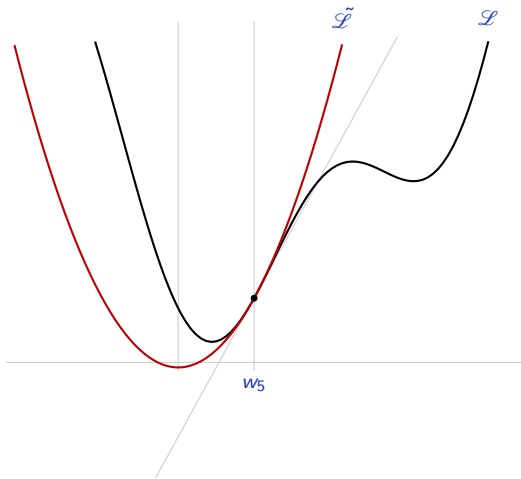
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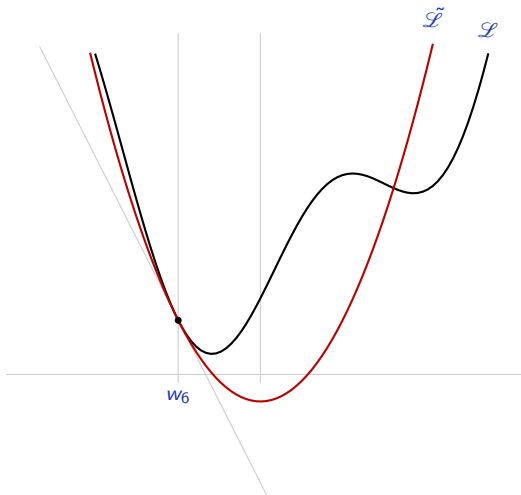


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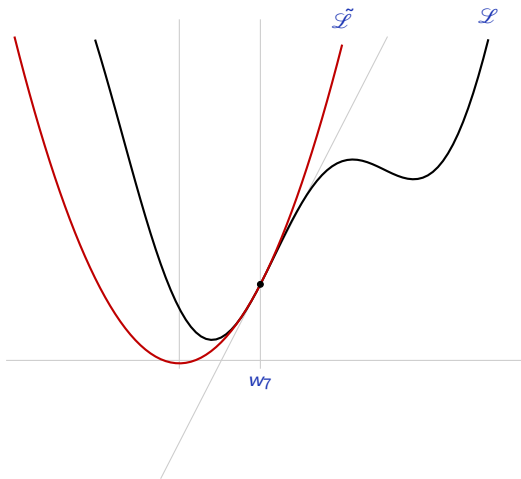




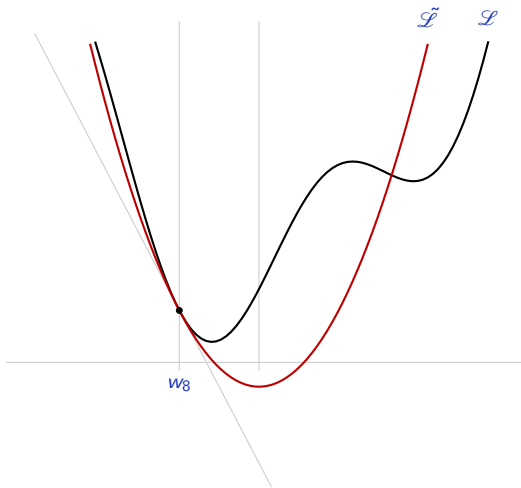
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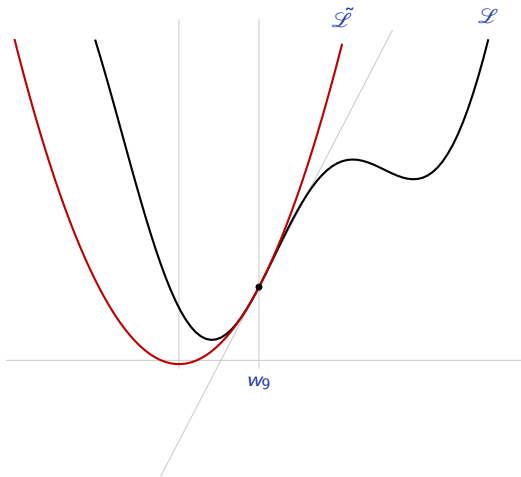
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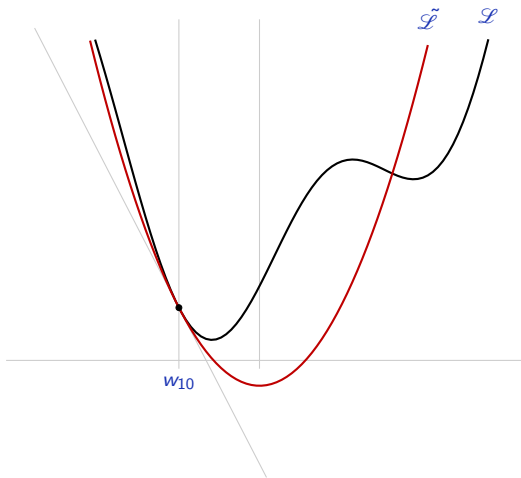
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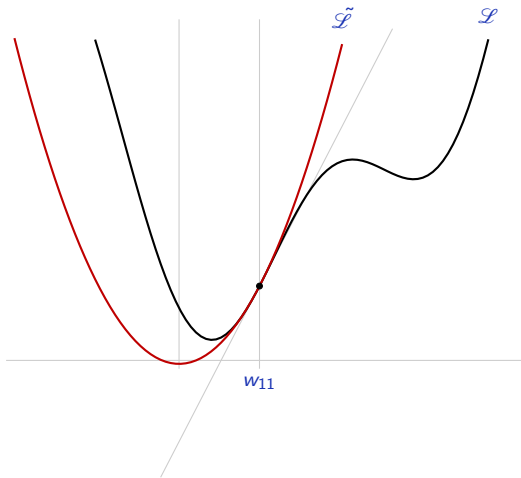
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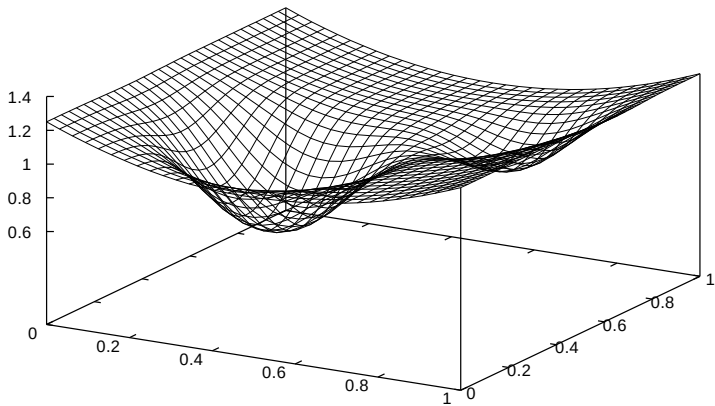


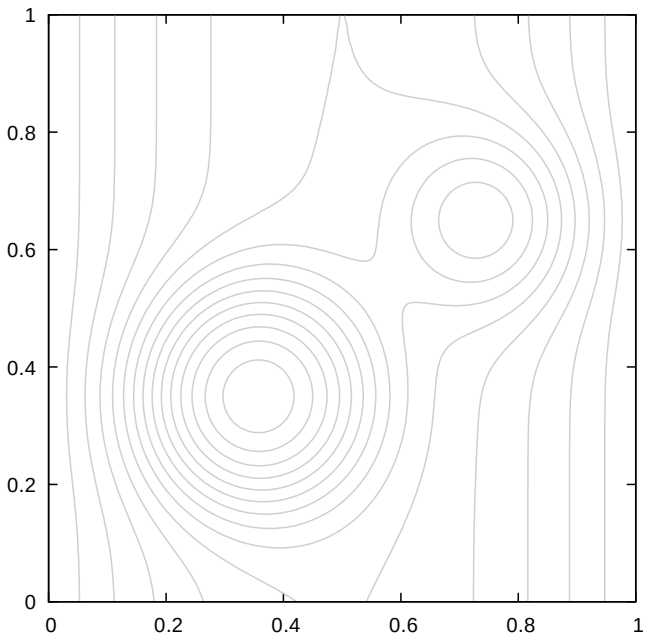
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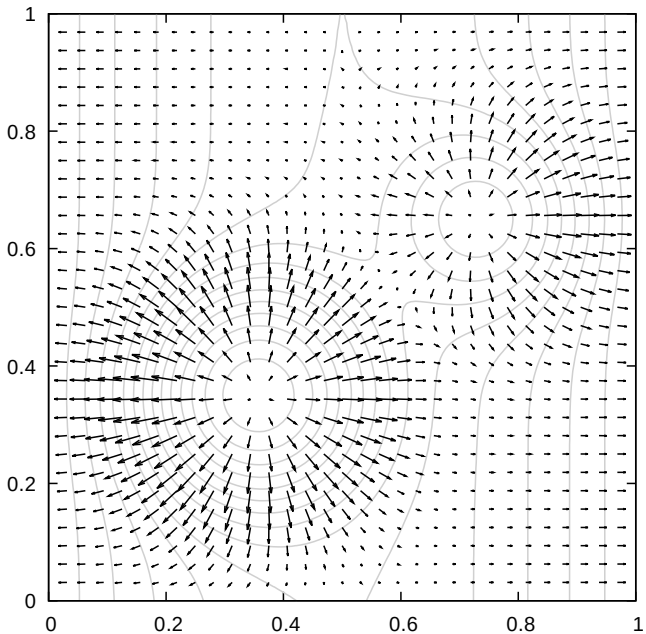
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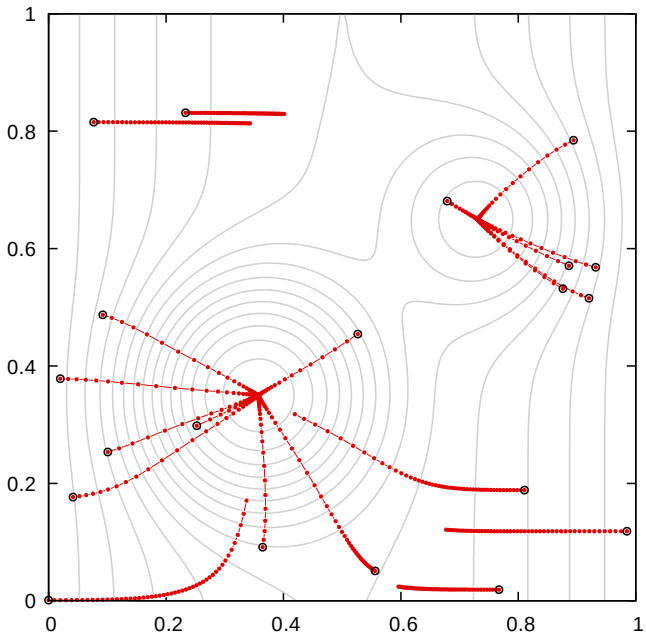












We saw that the minimum of the logistic regression loss

$$\mathcal{L}(w, b) = - \sum_n \log \sigma(y_n(w \cdot x_n + b))$$

does not have an analytic form.

We can derive

$$\frac{\partial \mathcal{L}}{\partial b} = - \sum_n \underbrace{y_n \sigma(-y_n(w \cdot x_n + b))}_{u_n},$$
$$\forall d, \frac{\partial \mathcal{L}}{\partial w_d} = - \sum_n \underbrace{x_{n,d} y_n \sigma(-y_n(w \cdot x_n + b))}_{v_{n,d}},$$

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which can be implemented as

```
def gradient(x, y, w, b):  
    u = y * (- y * (x.mv(w) + b)).sigmoid_  
    v = x * u.view(-1, 1) # Broadcasting  
    return - v.sum(0), - u.sum()
```

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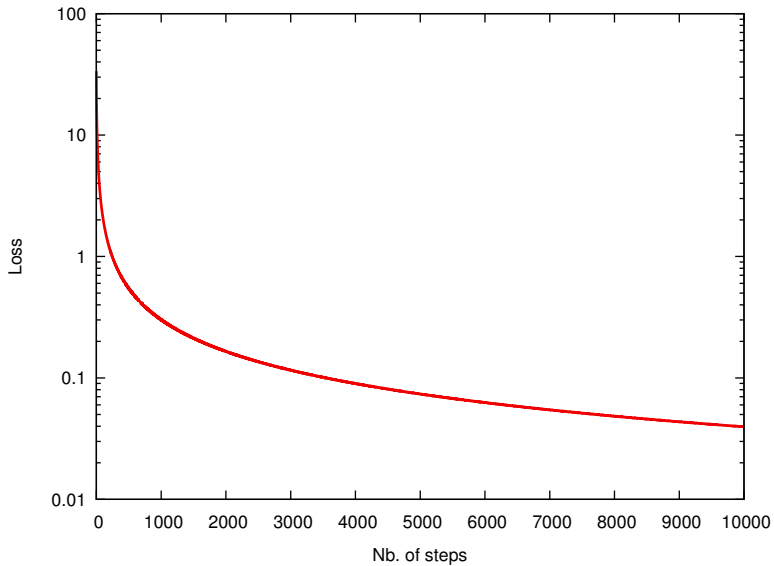
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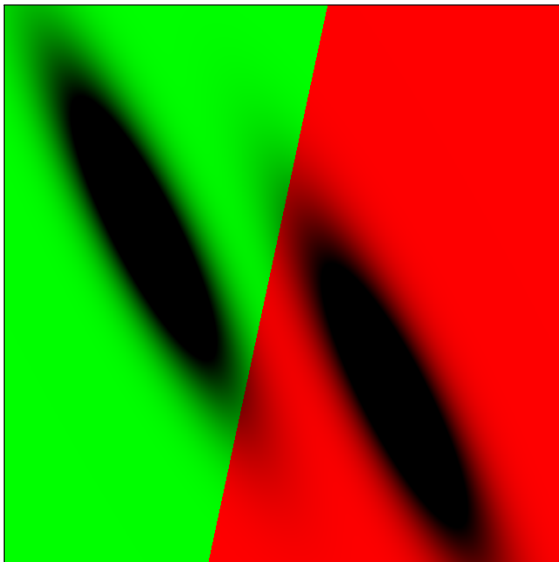
and the gradient descent as

```
w, b = torch.empty(x.size(1)).normal_(), 0  
eta = 1e-1
```

```
for k in range(nb_iterations):  
    dw, db = gradient(x, y, w, b)  
    w -= eta * dw  
    b -= eta * db
```



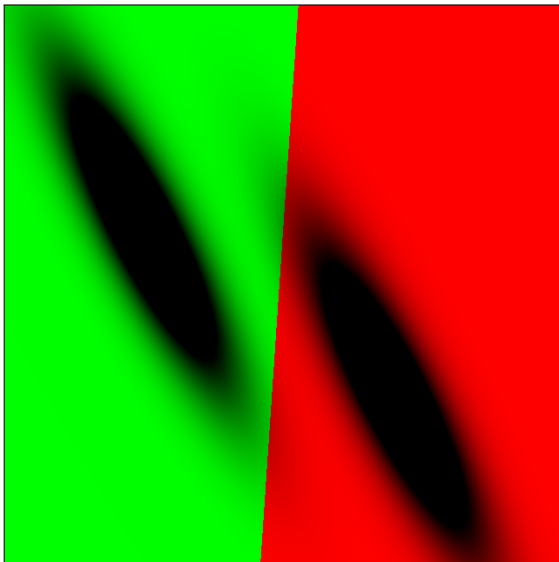
With 100 training points and  $\eta = 10^{-1}$ .



$n = 0$

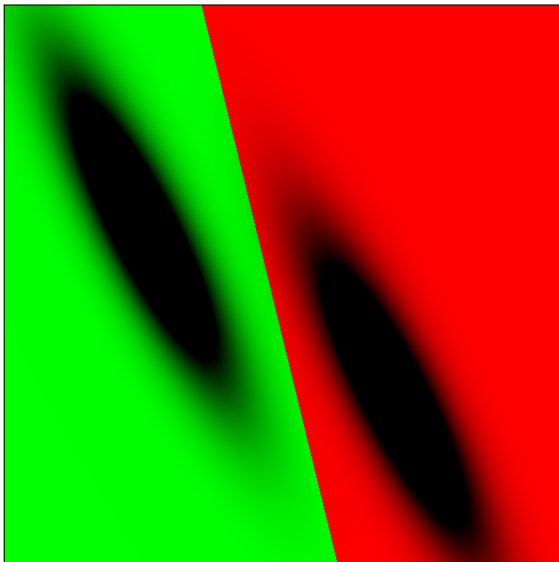


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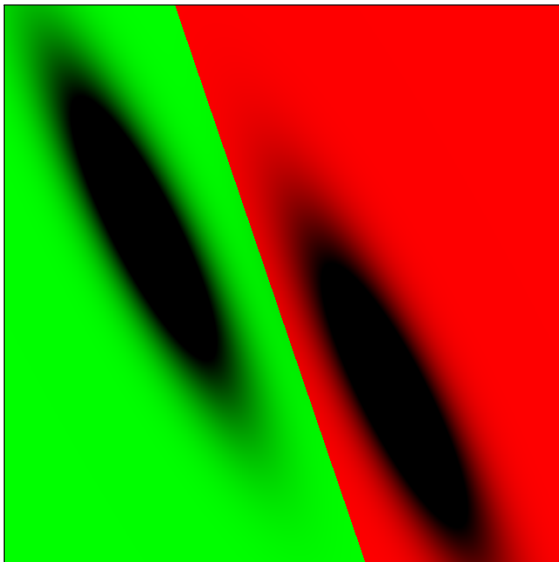
$n = 10$

With 100 training points and  $\eta = 10^{-1}$ .



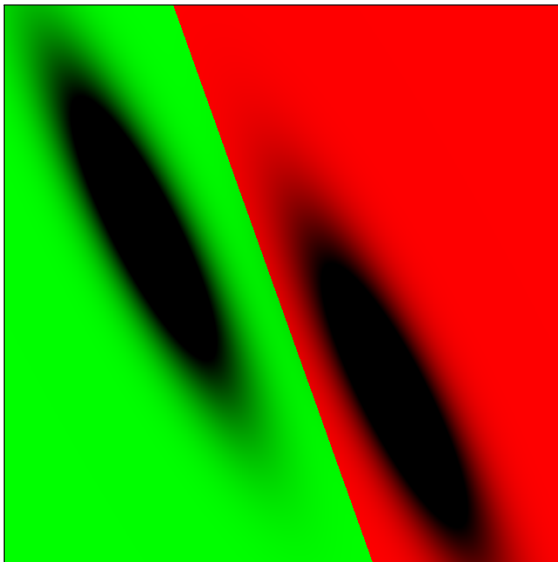
$n = 10^2$

With 100 training points and  $\eta = 10^{-1}$ .

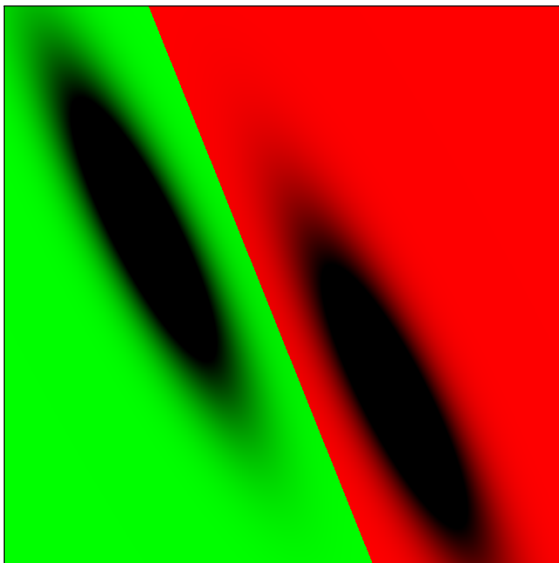


$n = 10^3$

With 100 training points and  $\eta = 10^{-1}$ .



$n = 10^4$



LDA

The end