

EE-559 – Deep learning

3.1. The perceptron

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Hence, **any Boolean function can be build with such units.**

(McCulloch and Pitts, 1943)

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$$f(x) = \begin{cases} 1 & \text{if } \sum_i w_i x_i + b \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

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This model was originally motivated by biology, with w_i being the *synaptic weights*, and x_i and f firing rates.

It is a (very) crude biological model.

(Rosenblatt, 1957)

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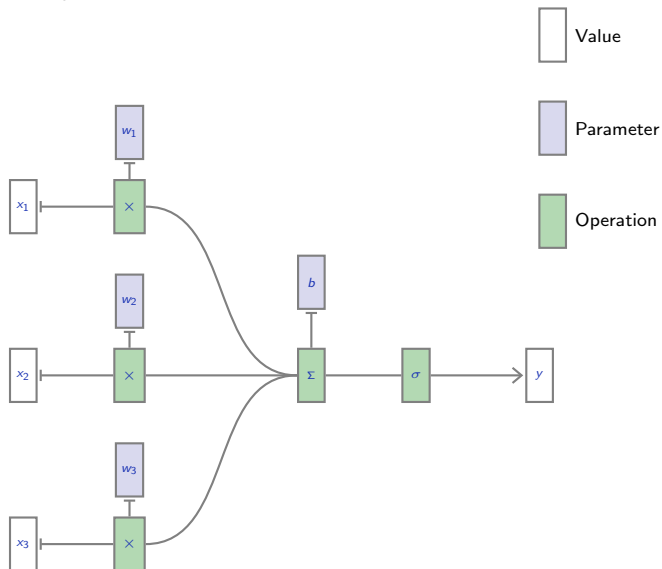


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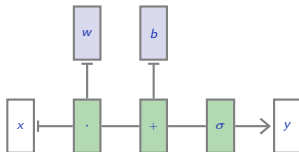
For neural networks, the function σ that follows a linear operator is called the **activation function**.

We can represent this “neuron” as follows:



We can also use tensor operations, as in

$$f(x) = \sigma(w \cdot x + b).$$



Given a training set

$$(x_n, y_n) \in \mathbb{R}^D \times \{-1, 1\}, \quad n = 1, \dots, N,$$

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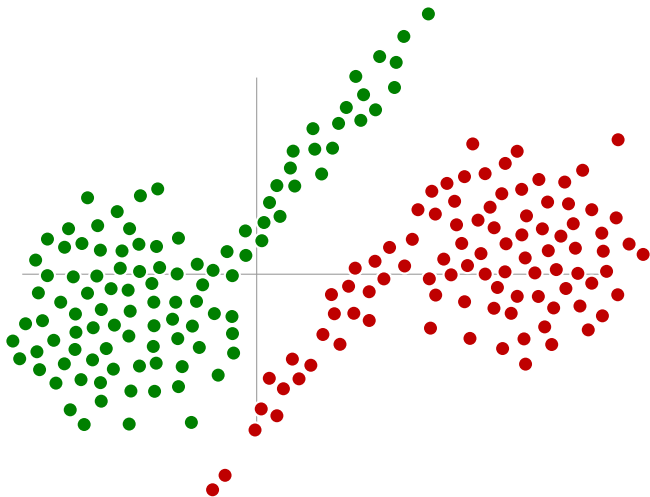
The bias b can be introduced as one of the w s by adding a constant component to x equal to 1.

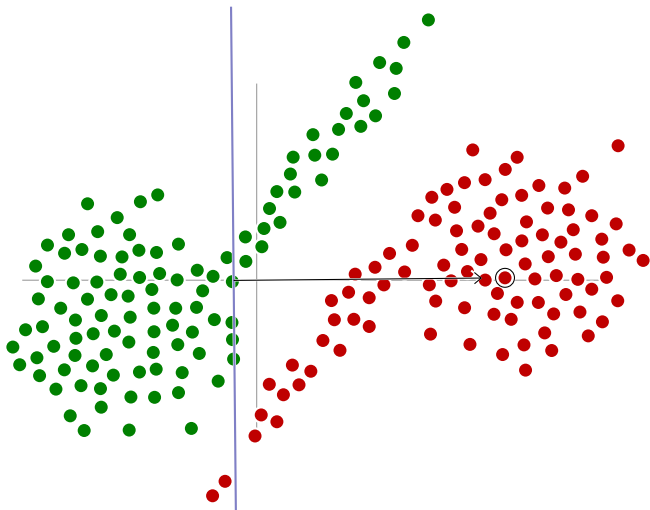
(Rosenblatt, 1957)

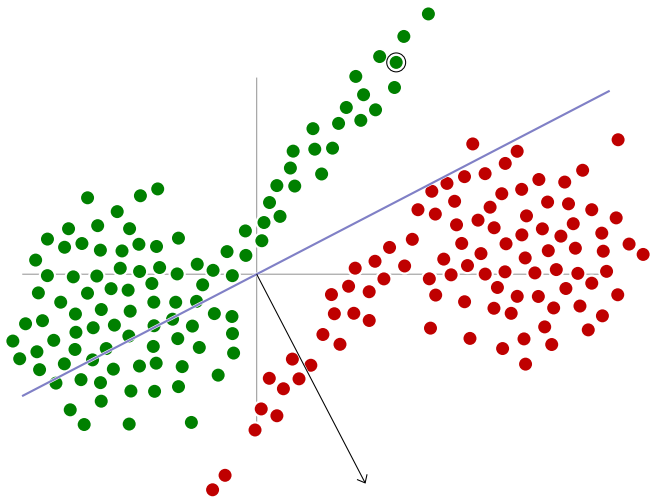
```
def train_perceptron(x, y, nb_epochs_max):
    w = torch.zeros(x.size(1))

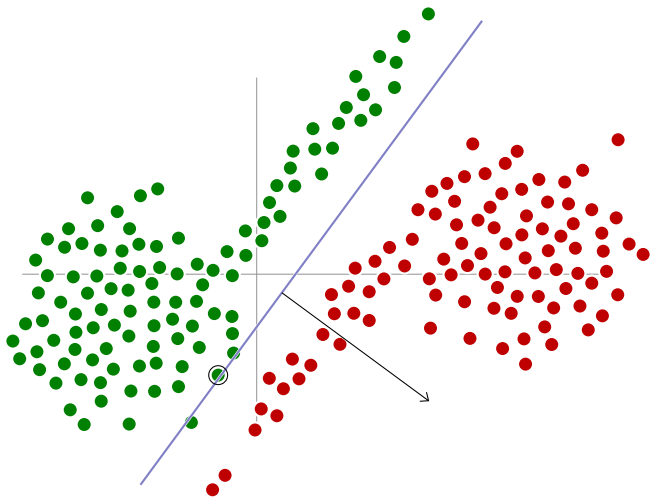
    for e in range(nb_epochs_max):
        nb_changes = 0
        for i in range(x.size(0)):
            if x[i].dot(w) * y[i] <= 0:
                w = w + y[i] * x[i]
                nb_changes = nb_changes + 1
        if nb_changes == 0: break;

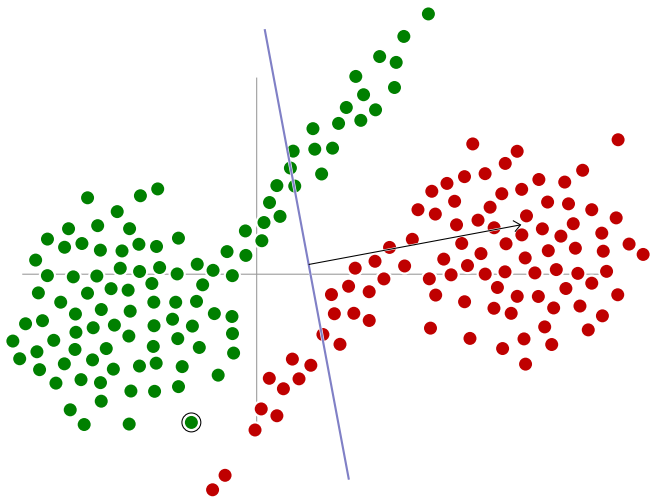
    return w
```

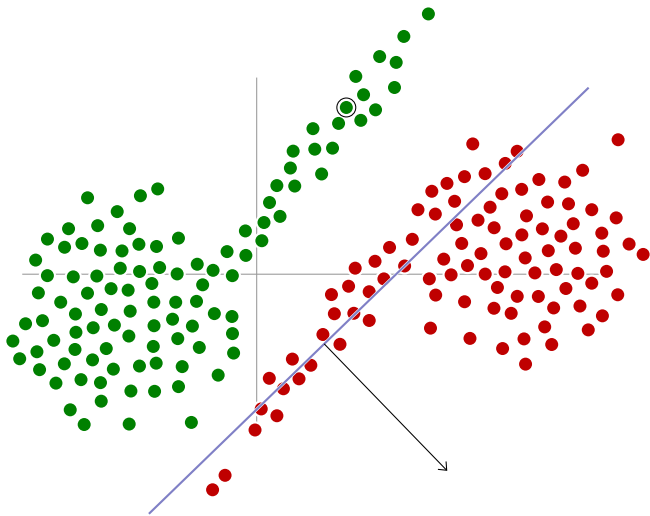


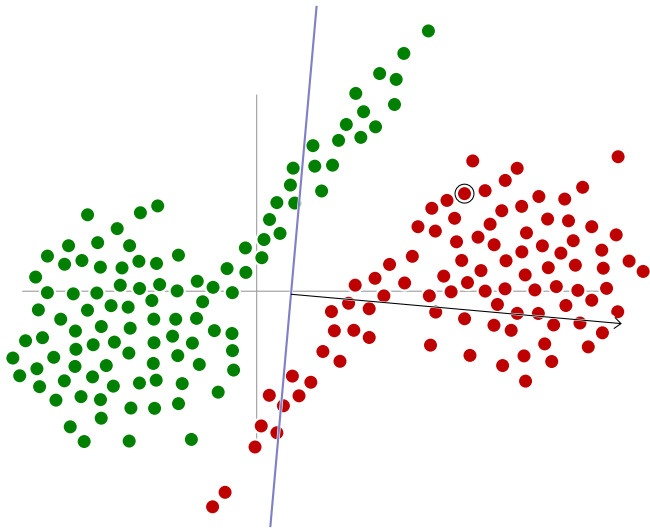


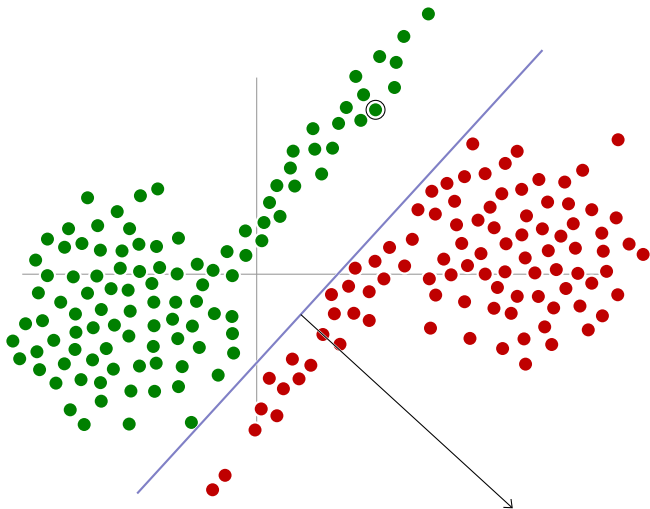








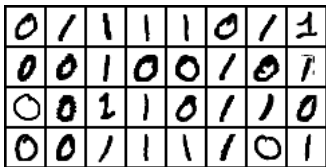




This crude algorithm works often surprisingly well. With MNIST's "0"s as negative class, and "1"s as positive one.

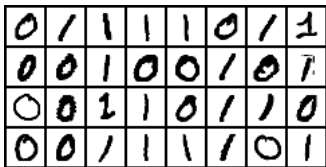
0	/	\			0	/	1
0	0	1	0	0	/	0	1
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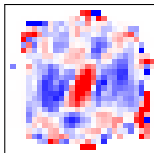


```
epoch 0 nb_changes 64 train_error 0.23% test_error 0.19%
epoch 1 nb_changes 24 train_error 0.07% test_error 0.00%
epoch 2 nb_changes 10 train_error 0.06% test_error 0.05%
epoch 3 nb_changes 6 train_error 0.03% test_error 0.14%
epoch 4 nb_changes 5 train_error 0.03% test_error 0.09%
epoch 5 nb_changes 4 train_error 0.02% test_error 0.14%
epoch 6 nb_changes 3 train_error 0.01% test_error 0.14%
epoch 7 nb_changes 2 train_error 0.00% test_error 0.14%
epoch 8 nb_changes 0 train_error 0.00% test_error 0.14%
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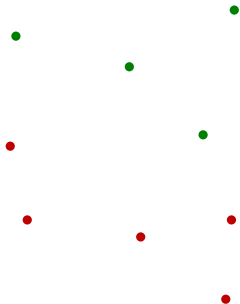

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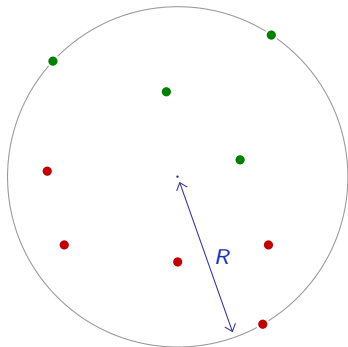
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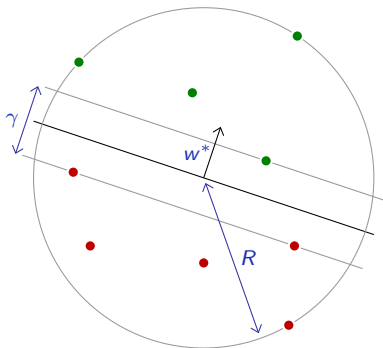


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2. The two populations can be separated with a margin $\gamma > 0$.
 $\exists w^*, \|w^*\| = 1, \exists \gamma > 0, \forall n, y_n (x_n \cdot w^*) \geq \gamma/2$.

To prove the convergence, let us make the assumption that there still is a misclassified sample at iteration k , and w^{k+1} is the weight vector updated with it. We have

$$\begin{aligned}w^{k+1} \cdot w^* &= (w^k + y_{n_k} x_{n_k}) \cdot w^* \\&= w^k \cdot w^* + y_{n_k} (x_{n_k} \cdot w^*) \\&\geq w^k \cdot w^* + \gamma/2 \\&\geq (k+1)\gamma/2.\end{aligned}$$

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Since

$$\|w^k\| \|w^*\| \geq w^k \cdot w^*,$$

we get

$$\begin{aligned}\|w^k\|^2 &\geq (w^k \cdot w^*)^2 / \|w^*\|^2 \\&\geq k^2 \gamma^2 / 4.\end{aligned}$$

And

$$\begin{aligned}\|w^{k+1}\|^2 &= w^{k+1} \cdot w^{k+1} \\ &= (w^k + y_{n_k} x_{n_k}) \cdot (w^k + y_{n_k} x_{n_k}) \\ &= w^k \cdot w^k + 2 \underbrace{y_{n_k} w^k \cdot x_{n_k}}_{\leq 0} + \underbrace{\|x_{n_k}\|^2}_{\leq R^2} \\ &\leq \|w^k\|^2 + R^2 \\ &\leq (k+1) R^2.\end{aligned}$$

Putting these two results together, we get

$$k^2 \gamma^2 / 4 \leq \|w^k\|^2 \leq k R^2$$

hence

$$k \leq 4R^2 / \gamma^2,$$

hence no misclassified sample can remain after $\lfloor 4R^2 / \gamma^2 \rfloor$ iterations.

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This result makes sense:

- The bound does not change if the population is scaled, and
- the larger the margin, the more quickly the algorithm classifies all the samples correctly.

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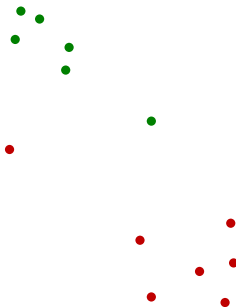
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Support Vector Machines (SVM) achieve this by minimizing

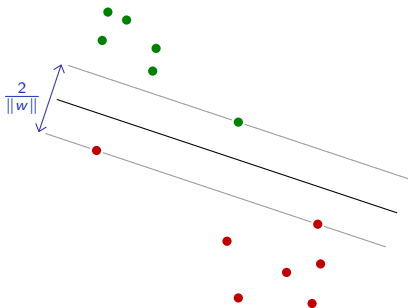
$$\mathcal{L}(w, b) = \lambda \|w\|^2 + \frac{1}{N} \sum_n \max(0, 1 - y_n(w \cdot x_n + b)),$$

which is convex and has a global optimum.

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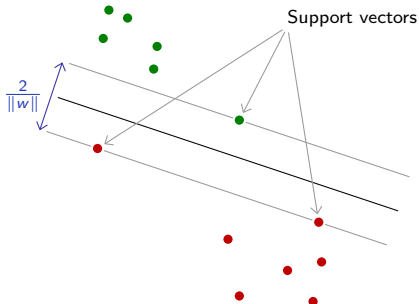


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Minimizing $\max(0, 1 - y_n(w \cdot x_n + b))$ pushes the n th sample beyond the plane $w \cdot x + b = y_n$, and minimizing $\|w\|^2$ increases the distance between the $w \cdot x + b = \pm 1$.

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At convergence, only a small number of samples matter, the “support vectors”.

The term

$$\max(0, 1 - \alpha)$$

is the so called “hinge loss”



The end

References

- W. S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4):115–133, 1943.
- F. Rosenblatt. The perceptron—A perceiving and recognizing automaton. Technical Report 85-460-1, Cornell Aeronautical Laboratory, 1957.