Linear Methods 1

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February 2023

- Welcome, introduction
- The supervised learning problem
- Perceptron: classification with a linear model

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What should the bank, trading firm, and website do? Learn a predictive model.

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$$D \longrightarrow \boxed{\text{Supervised Learning Algorithm}} \longrightarrow \text{Model}.$$

• Using the model on new x (not necessarily present in D) to predict y.

$$x \longrightarrow \boxed{\mathsf{Model}} \longrightarrow y.$$

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- Ordinal features take discrete values that can be ordered.
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- If the class label is categorical, the task is a classification task.
 If the class label is numeric, the task is a regression task.
 For now, we'll assume all features are numeric. Reasonable assumption?

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 No. There are many good, open-source implementations to choose from. But it will still take time to analyse and iterate and refine.

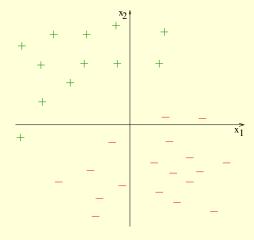
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- What are some challenges involved in supervised learning?
 Preparing the data set, handling missing/noisy fields, class imbalance, etc.

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- Perceptron: classification with a linear model

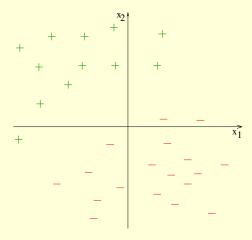
Perceptron Learning Algorithm

• Illustration with d = 2 features (x_1, x_2) , 2 classes ("+" or 1, "-" or -1).



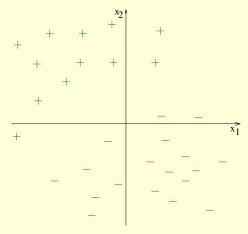
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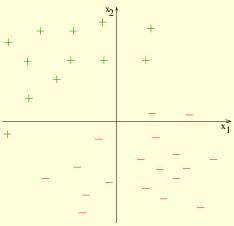
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- Assumption: Data is linearly separable, by a line passing through the origin.

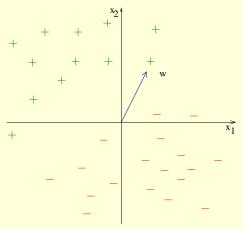


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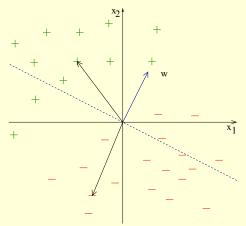
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- How to find such a line (in higher dimensions, a hyperplane)?





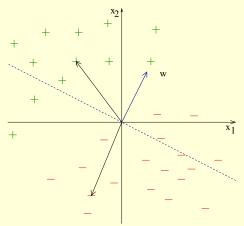


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- ▶ assign label "+" if $w \cdot x \ge 0$;
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By a vector $w = (w_1, w_2)$. For point x,

- ▶ assign label "+" if $w \cdot x > 0$;
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Now how to find a satisfying *w*?

Perceptron Learning Algorithm

Initialise w arbitrarily. (Recall that it is a *d*-dimensional vector.)

While there is some misclassified point:

Select an arbitrary misclassified point (x, y). //That means y = 1 but $w \cdot x < 0$, or y = -1 but $w \cdot x \ge 0$.

Set
$$w \leftarrow w + yx$$
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Return w.

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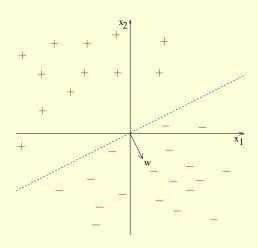
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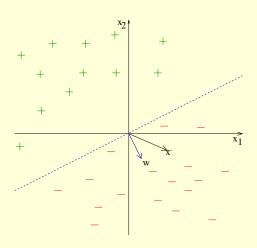
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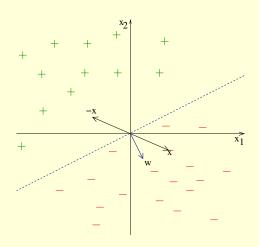
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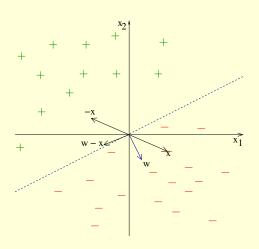
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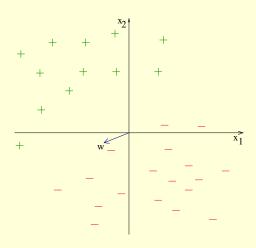
That's it!

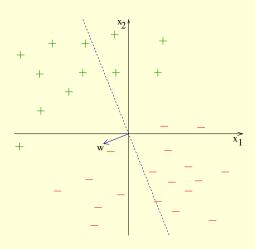


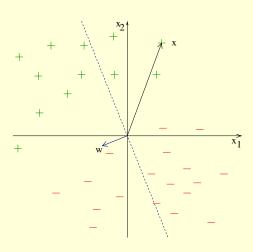


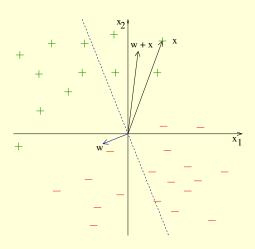


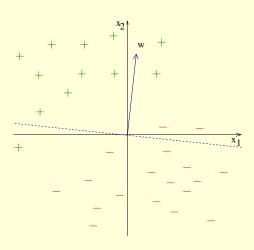


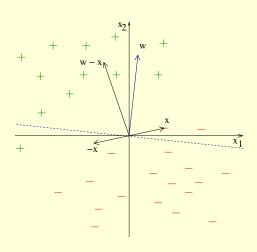


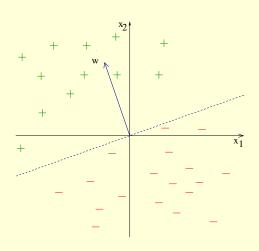












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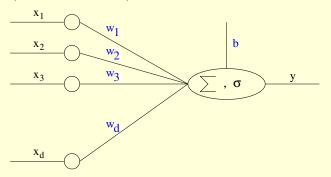
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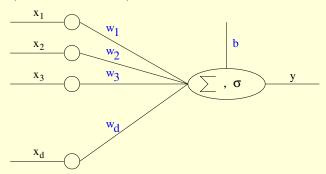
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- Why is it called a *Perceptron*? (Is it related to electrons and neutrons?!)

Perceptron (Rosenblatt, 1957)



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- An early version was built in hardware.
- $y = \text{sign}(w_1x_1 + w_2x_2 + \cdots + w_dx_d + b)$, where $\text{sign}(\alpha) = \begin{cases} 1 & \text{if } \alpha \geq 0 \\ -1 & \text{otherwise.} \end{cases}$

b is the "bias", which we had assumed to be 0, but which is also easy to learn.

References

 Chapter 4, A Course in Machine Learning, Hal Daumé III. Available on-line at http://ciml.info/.