Introduction to Online Learning Algorithms

Yoav Freund

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Outline

Example trace for Halving Algorithm

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expert1
expert2
expert3
expert4
expert5
expert6
expert7
expert8

alg.

Example trace for Halving Algorithm

expert1
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outcome

Example trace for Halving Algorithm

	$t = 1$
expert1	1
expert2	1
expert3	0
expert4	1
expert5	1
expert6	0
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expert7	1
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alg.	1
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Example trace for Halving Algorithm

	$t = 1$	$t = 2$
expert1	1	1
expert2	1	0
expert3	0	-
expert4	1	0
expert5	1	0
expert6	0	-
expert7	1	1
expert8	1	1
alg.	1	
outcome	1	

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	$t = 1$	$t = 2$
expert1	1	1
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expert1	1	1
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expert6	0	-
expert7	1	1
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Example trace for Halving Algorithm

	$t = 1$	$t = 2$	$t = 3$
expert1	1	1	1
expert2	1	0	-
expert3	0	-	-
expert4	1	0	-
expert5	1	0	-
expert6	0	-	-
expert7	1	1	1
expert8	1	1	1
alg.	1	0	
outcome	1	1	

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	$t = 1$	$t = 2$	$t = 3$
expert1	1	1	1
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expert3	0	-	-
expert4	1	0	-
expert5	1	0	-
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	$t = 1$	$t = 2$	$t = 3$	$t = 4$
expert1	1	1	1	1
expert2	1	0	-	-
expert3	0	-	-	-
expert4	1	0	-	-
expert5	1	0	-	-
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Example trace for Halving Algorithm

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
expert1	1	1	1	1	-
expert2	1	0	-	-	-
expert3	0	-	-	-	-
expert4	1	0	-	-	-
expert5	1	0	-	-	-
expert6	0	-	-	-	-
expert7	1	1	1	1	0
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outcome	1	1	1	0	

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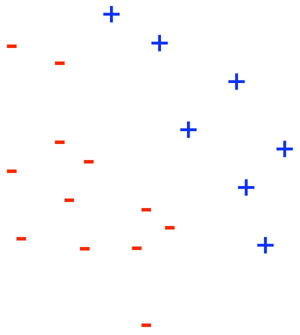
- Each time algorithm makes a mistakes, the pool of perfect experts is halved (at least).
- We assume that at least one expert is perfect.
- Number of mistakes is at most $\log_2 N$.
- No stochastic assumptions whatsoever.
- Proof is based on combining a lower and upper bounds on the number of perfect experts.

The Perceptron Problem

The Perceptron Problem



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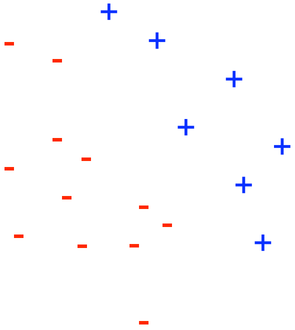

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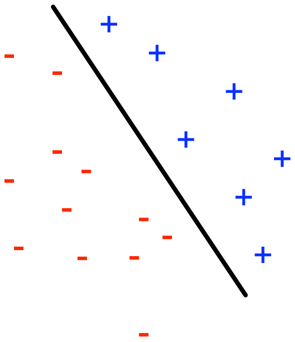

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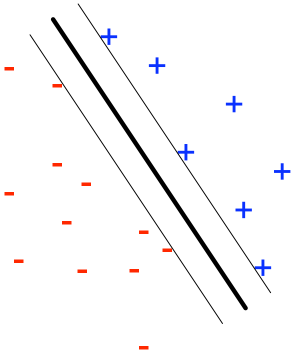

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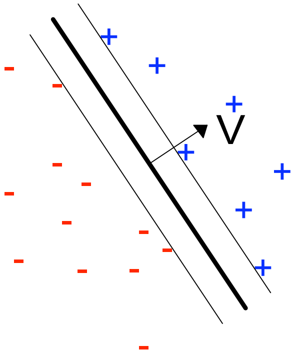

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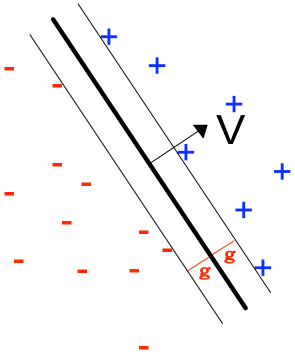

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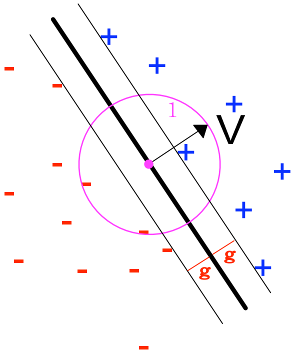

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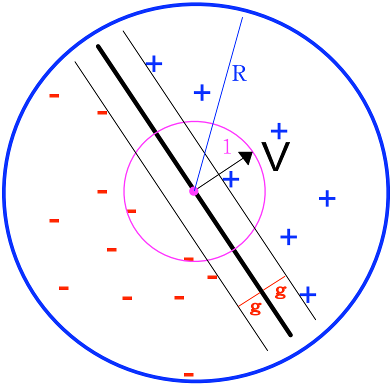

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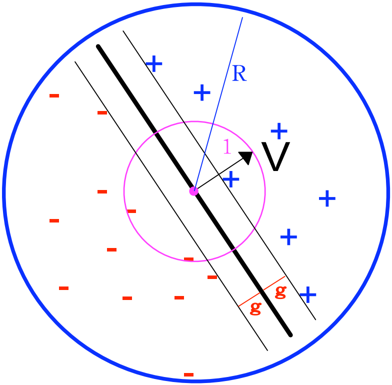

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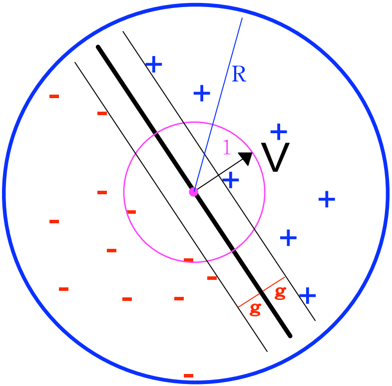

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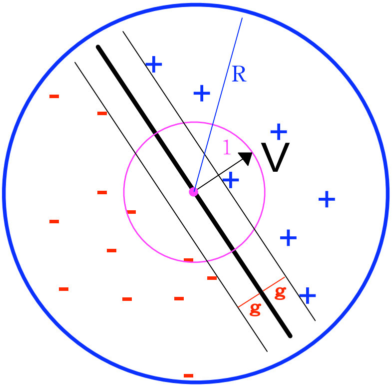

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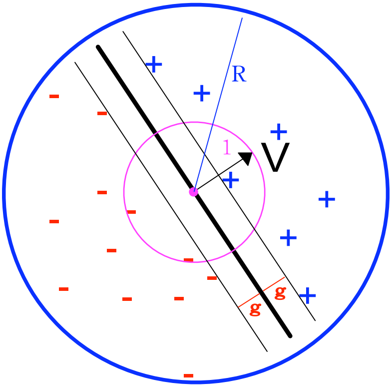

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- Example = $(\vec{X}, y)$, $y \in \{-1, +1\}$.
- $\forall \vec{X},\ \ \|\vec{X}\| \leq R$.
- $\forall (\vec{X}, y)$, $y(\vec{X} \cdot \vec{V}) \geq g$

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- An online algorithm. Examples presented one by one.

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- An online algorithm. Examples presented one by one.
- start with $\vec{W}_0 = \vec{0}$.
- If mistake: $(\vec{W}_i \cdot \vec{X}_i)y_i \leq 0$
    - Update $\vec{W}_{i+1} = \vec{W}_i + y_i X_i$.

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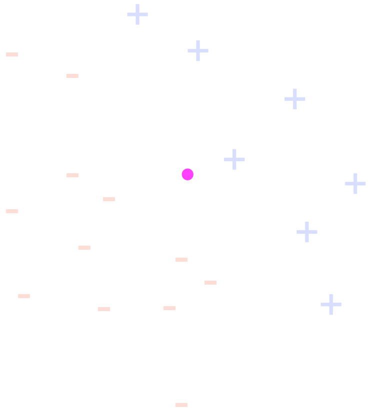

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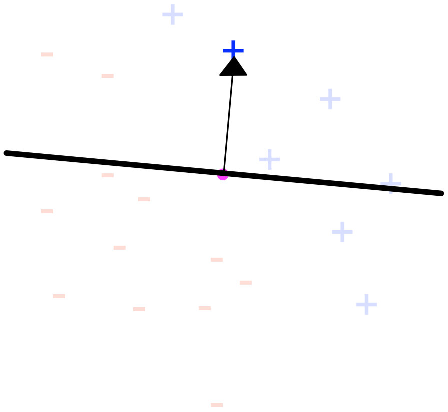

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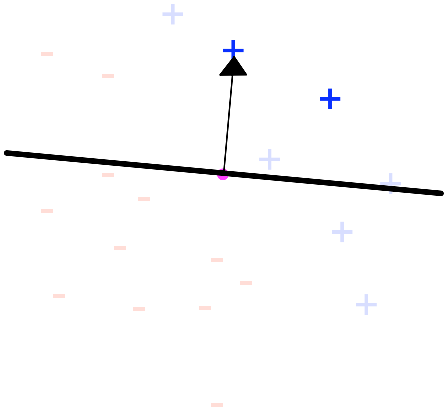

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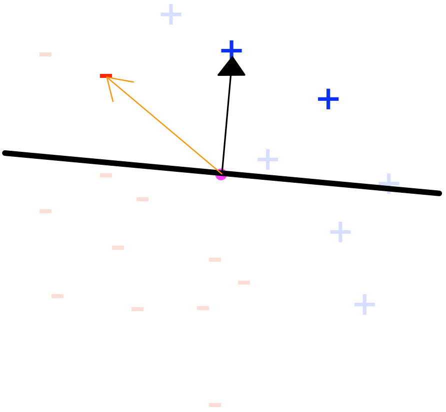

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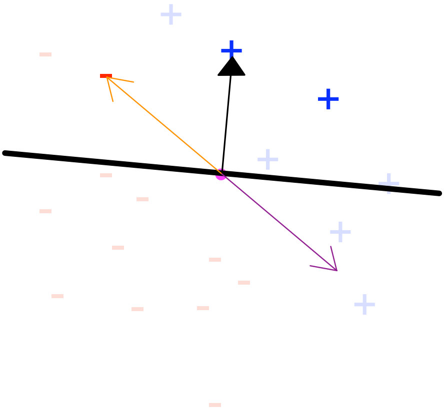

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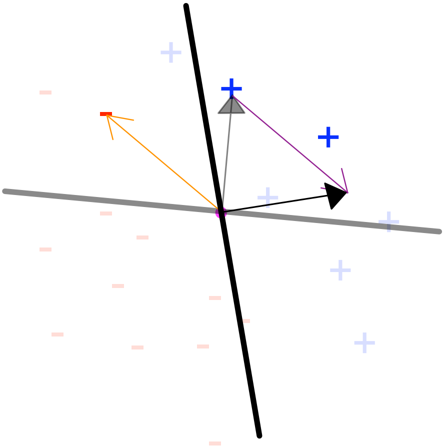

Bound on number of mistakes

- The number of mistakes that the perceptron algorithm can make is at most $\left(\frac{R}{g}\right)^2$.

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- Proof by combining upper and lower bounds on $\|\vec{W}\|$.

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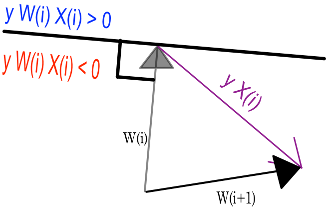

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  $\|\vec{W}_{i+1}\|^2 \leq \|\vec{W}_i\|^2 + \|\vec{X}_i\|^2$
  $\leq \|\vec{W}_i\|^2 + R^2 \leq (i + 1)R^2$

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  $\geq ig + g = (i + 1)g$

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Thus:

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- Impossible without additional constraints.

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- Online prediction: predict x_{t+1} from $Y^t = \langle Y_1, Y_2, \ldots, Y_t \rangle$.
- **Expected regret**: compare performance of algorithm to Regret $= \mathrm{E}_{Y^T} \left[(x_t - Y_t)^2 \right] - \sigma^2$

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  $\text{Regret}_T = \sum_{t=1}^{T} (x_t - y_t)^2 - \sum_{t=1}^{T} (x_T^* - y_t)^2$
- **Goal:** sublinear regret $\lim_{T \to \infty} \frac{\text{Regret}_T}{T} = 0$

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- $x_{t+1} = \operatorname{argmin}_{x \in [0,1]} \sum_{i=1}^{t} (x - y_i)^2$
- We will prove that the regret of this algorithm is upper bound by $4 + 4 \ln T$

A more general setup

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- Regret relative to $\mathbf{u} \in V$: $\text{Regret}_T = \sum_{t=1}^{T} \ell_t(\mathbf{x}_t) - \sum_{t=1}^{T} \ell_t(\mathbf{u})$

Technical Lemma

Lemma

Let $\mathbf{x}_t^*$ be the minimizer of $\sum_{i=1}^{t} \ell_i(\mathbf{x})$. Then
$\sum_{t=1}^{T} \ell_t(\mathbf{x}_t^*) \leq \sum_{t=1}^{T} \ell_t\left(\mathbf{x}_T^*\right)$

regret bound

Theorem

Let $y_t \in [0, 1]$ *for* $t = 1, \ldots T$ *an arbitrary sequence of numbers. Let the algorithm output be* $x_t = x^*_{t-1} = \frac{1}{t-1}\sum_{i=1}^{t-1} y_i$*, then*

$$Regret_T = \sum_{t=1}^{T}(x_t - y_t)^2 - \sum_{t=1}^{T}(x^*_T - y_t)^2 \leq 4 + 4 \ln T$$

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- HW for next monday: prove the theorem.