Introduction to Online Learning Algorithms

Yoav Freund

January 2, 2020

Outline

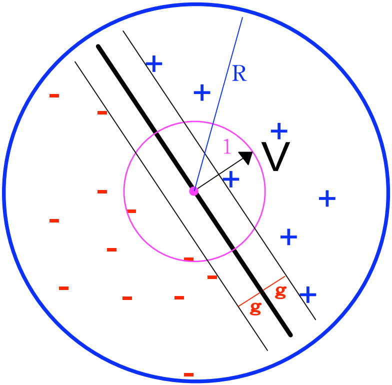
Example trace for Halving Algorithm

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
expert1	1	1	1	1	-
expert2	1	0	-	-	-
expert3	0	-	-	-	-
expert4	1	0	-	-	-
expert5	1	0	-	-	-
expert6	0	-	-	-	-
expert7	1	1	1	1	0
expert8	1	1	1	0	-
alg.	1	0	1	1	0
outcome	1	1	1	0	0

Mistake bound for Halving algorithm

- 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

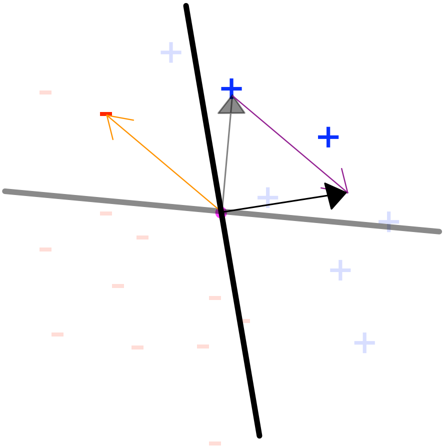


- $\|\vec{V}\| = 1$
- Example = $(\vec{X}, y)$, $y \in \{-1, +1\}$.
- $\forall \vec{X},\ \ \|\vec{X}\| \leq R$.
- $\forall (\vec{X}, y)$, $y(\vec{X} \cdot \vec{V}) \geq g$

The Perceptron learning algorithm

- 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 $\vec{W}_{i+1} = \vec{W}_i + y_i X_i$.

Example trace for the perceptron algorithm



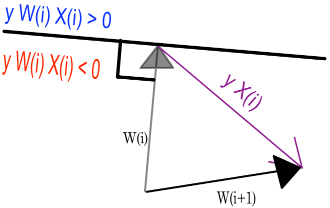
Bound on number of mistakes

- The number of mistakes that the perceptron algorithm can make is at most $\left(\frac{R}{g}\right)^2$.
- Proof by combining upper and lower bounds on $\|\vec{W}\|$.

Pythagorian Lemma

If $(\vec{W}_i \cdot X_i)y < 0$ then

$$\|\vec{W}_{i+1}\|^2 = \|\vec{W}_i + y_i \vec{X}_i\|^2 \leq \|\vec{W}_i\|^2 + \|\vec{X}_i\|^2$$



Upper bound on $\|\vec{W}_i\|$

Proof by induction

- Claim: $\|\vec{W}_i\|^2 \leq iR^2$
- Base: $i = 0$, $\|\vec{W}_0\|^2 = 0$
- Induction step (assume for i and prove for $i + 1$):
  $\|\vec{W}_{i+1}\|^2 \leq \|\vec{W}_i\|^2 + \|\vec{X}_i\|^2$
  $\leq \|\vec{W}_i\|^2 + R^2 \leq (i + 1)R^2$

Lower bound on $\|\vec{W}_i\|$

$\|\vec{W}_i\| \geq \vec{W}_i \cdot \vec{V}$ because $\|\vec{V}\| = 1$.
We prove a lower bound on $\vec{W}_i \cdot \vec{V}$ using induction over i

- Claim: $\vec{W}_i \cdot \vec{V} \geq ig$
- Base: $i = 0$, $\vec{W}_0 \cdot \vec{V} = 0$
- Induction step (assume for i and prove for $i + 1$):
  $\vec{W}_{i+1} \cdot \vec{V} = \left(\vec{W}_i + \vec{X}_i y_i\right) \vec{V} = \vec{W}_i \cdot \vec{V} + y_i \vec{X}_i \cdot \vec{V}$
  $\geq ig + g = (i + 1)g$

Combining the upper and lower bounds

$$(ig)^2 \leq \|\vec{W}_i\|^2 \leq iR^2$$

Thus:

$$i \leq \left(\frac{R}{g}\right)^2$$

The mean estimation game

- An adversary choses a real number $y_t in[0, 1]$ and keeps it secret.
- You make a guess of the secret number x_t
- The adversary reveals the secret and you pay $(x_t - y_t)^2$
- You want to minimize $\frac{1}{T}\sum_{t=1}^{T}(x_t - y_t)^2$
- Impossible without additional constraints.

Adversary is a fixed distribution

- Suppose that the adversary draws $y_1, y_2, \ldots, y_T$ IID from a fixed distribution over $[0, 1]$ with mean μ and std σ.
- Optimal prediction $x_t = \mu$
- $\mathrm{E}_Y \left[(\mu - Y)^2 \right] = \sigma^2$
- 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 $= \mathrm{E}_{Y^T} \left[(x_t - Y_t)^2 \right] - \sigma^2$

Individual sequence bounds

- Make no assumption about how the sequence is generated.
- The best constant value for x in hind-sight:

$$x_T^* \doteq \operatorname*{argmin}_{x \in [0,1]} \sum_{t=1}^{T} (x - y_t)^2, \quad x_t^* = \frac{1}{T} \sum_{t=1}^{T} X_t$$

- Regret: the loss over and above the loss of x_T^*. **for the worst-case sequence**
  $\text{Regret}_T = \sum_{t=1}^{T} (x_t - y_t)^2 - \sum_{t=1}^{T} (x_T^* - y_t)^2$
- **Goal:** sublinear regret $\lim_{T \to \infty} \frac{\text{Regret}_T}{T} = 0$

Follow the Leader

- Idea: set x_{t+1} to be the best constant prediction on $y_1, \ldots, y_t$
- $x_{t+1} = \operatorname{argmin}_{x \in [0,1]} \sum_{i=1}^{t} (x - y_i)^2$
- We will prove that the regret of this algorithm is upper bound by $4 + 4 \ln T$

A more general setup

- General euclidean space: $\mathbf{x}, \mathbf{y}$ are elements in $V \subset \mathbb{R}^d$
- The loss function for time step t maps $\mathbf{x}$ to $\mathbb{R}$: $\ell_t : V \to \mathbb{R}$
- For square loss: $\ell_t(\mathbf{x}) = (\mathbf{x} - \mathbf{y}_t)^2$
- 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*

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