Exponential Weights Algorithms for Online Learning

Yoav Freund

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- **Weak PAC Learning**: Same as strong PAC, but only required to hold for a single $\epsilon < \frac{1}{2}$.

Boosting

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- How it is done: by giving the weak learner different distributions.

Zero sum games in matrix form

- Game between two players.

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- Game repeated many times.

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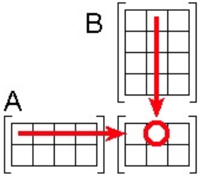
Mixed strategies in matrix notation



$$(A \times B)_{12} = \sum_{r=1}^{4} a_{1r} b_{r2} = a_{11}b_{12} + a_{12}b_{22} + a_{13}b_{32} + a_{14}b_{42}$$

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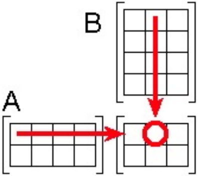

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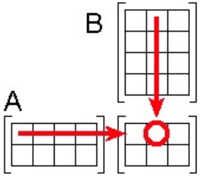

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Q is a column vector. $\mathbf{P}^T$ is a row vector.

$$\mathbf{M}(\mathbf{P},\mathbf{Q}) = \mathbf{P}^T\mathbf{M}\mathbf{Q} = \sum_{i=1}^{n} \sum_{j=1}^{m} \mathbf{P}(i)\mathbf{M}(i,j)\mathbf{Q}(j)$$

The minmax Theorem

When using pure strategies, second player has an advantage.

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John von Neumann, 1928.

$$\min_{\mathbf{P}} \max_{\mathbf{Q}} \mathbf{M}(\mathbf{P}, \mathbf{Q}) = \max_{\mathbf{Q}} \min_{\mathbf{P}} \mathbf{M}(\mathbf{P}, \mathbf{Q})$$

In words: for mixed strategies, choosing second gives no advantage.

The learning game matrix

	Example 1	Example 2	Example 3
Rule 1	0	1	0
Rule 2	1	1	0
Rule 3	0	0	1
Rule 4	1	0	1
Rule 5	0	1	1

entries: 1 = rule is correct on example, 0= incorrect

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- For any distribution **Q** over the examples there exists a row (rule) that is correct on $\frac{1}{2} + \gamma$ of the (dist over the) examples.

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- The weighted majority is always correct.
- Existence proof, but not an algorithm.

Schapire's boosting algorithm

Calls the weak learner 3 times, on 3 different distributions, combines the rules using a majority.
The distributions are

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- h_3 Filter out examples such that $h_1(x) = h_2(x)$

Idea of proof

- If errors of weak rules are at most $x < 1/2$ then error of combined rule is at most $3x^2 - 2x^3$.

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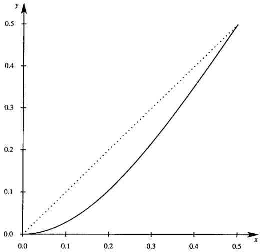

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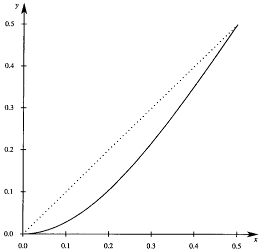

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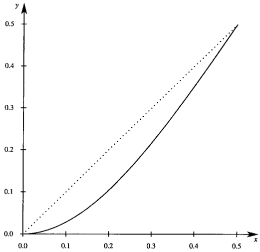

- *Figure 1.* A graph of the function $g(x) = 3x^2 - 2x^3$.
- Let the available rules have error $\frac{1}{2} - \gamma$ and assume we want a rule whose error is ϵ.
- Using 3-combiner recursively for depth at most $O(\frac{1}{\gamma^2} \log \frac{1}{\epsilon})$ achieves the error ϵ.

Boost By Majority

Majority vote over many weak rules, rather than 3.

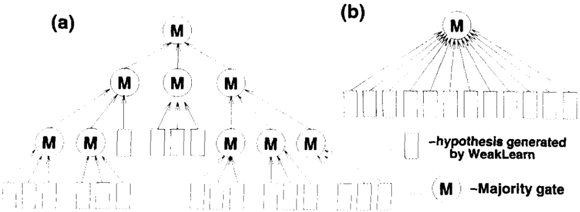

FIG. 1. Final concepts structure: (a) Schapire, (b) a one-layer majority circuit.

Game between booster and learner

- Booster chooses distribution over examples.

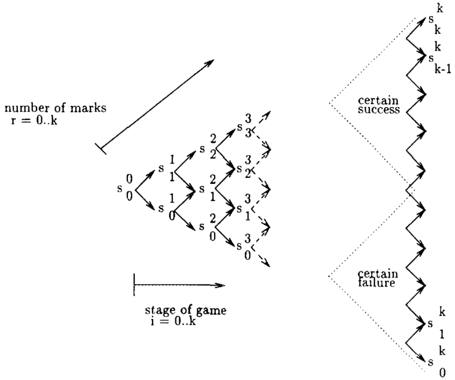

FIG. 2. Transitions between consecutive partitions.

Game between booster and learner

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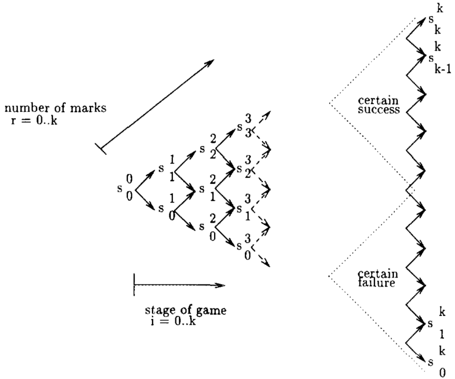

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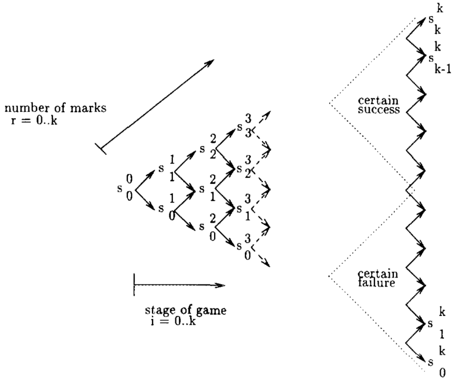
- Weak learner constrained to make weighted error smaller than $(1/2) - \gamma$



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Potential function

loss set and which are in the reward set; it is reasonable to define the potential for $i = k$ as

$$\beta_r^k = \begin{cases} 0 & \text{if} \quad r > \dfrac{k}{2} \\ 1 & \text{if} \quad r \leqslant \dfrac{k}{2}. \end{cases} \tag{4}$$

For $i < k$ we define the potential recursively:

$$\beta_r^i = (\tfrac{1}{2} - \gamma)\, \beta_r^{i+1} + (\tfrac{1}{2} + \gamma)\, \beta_{r+1}^{i+1}. \tag{5}$$

Weight function

The weighting factor is defined inductively as

$$\alpha_r^{k-1} = \begin{cases} 1 & \text{if } \quad r = \left\lfloor \frac{k}{2} \right\rfloor \\ 0 & \text{otherwise.} \end{cases}$$

and for $0 \leqslant i \leqslant k-2$,

$$\alpha_r^i = \left(\tfrac{1}{2} - \gamma\right) \alpha_r^{i+1} + \left(\tfrac{1}{2} + \gamma\right) \alpha_{r+1}^{i+1}.$$

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- Idea of proof, consider last and next to last steps.

Error bound

Given a weak learner with error $(1/2) - \gamma$, find k that satisfies

$$\sum_{j=0}^{\lfloor \frac{k}{2} \rfloor} \binom{k}{j} \left(\frac{1}{2} + \gamma\right)^j \left(\frac{1}{2} - \gamma\right)^{k-j} \leq \epsilon.$$

Then running Boost-by-majority for k iterations will generate a rule with error at most ϵ.

Adaboost

Algorithm AdaBoost (Setup)

Input:

- Sequence of N labeled examples $\langle (x_1, y_1), \ldots, (x_N, y_N) \rangle$

Initialize:

$$w_i^1 = \frac{1}{N} \quad \text{for } i = 1, \ldots, N.$$

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- Integer T specifying number of iterations

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For $t = 1, 2, \ldots, T$:

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$$\epsilon_t = \sum_{i=1}^{N} p_i^t \mid h_t(x_i) - y_i \mid .$$

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4. Set
$$\beta_t = \frac{\epsilon_t}{1 - \epsilon_t}.$$
5. Update the weights:
$$w_i^{t+1} = w_i^t \, \beta_t^{\left(1 - \mid h_t(x_i) - y_i \mid\right)} .$$

Algorithm AdaBoost (Final Output)

Output the final hypothesis h_{final}, defined by:

$$h_{final}(x) = \begin{cases} 1, & \text{if } \sum_{t=1}^{T} \left(\ln \frac{1}{\beta_t}\right) h_t(x) \ \geq \ \frac{1}{2} \sum_{t=1}^{T} \ln \frac{1}{\beta_t}, \\ 0, & \text{otherwise.} \end{cases}$$

Main Theorem

Theorem 6 Suppose the weak learning algorithm WeakLearn, when called by AdaBoost, generates hypotheses with errors $\epsilon_1, \ldots, \epsilon_T$. Then the error $\epsilon = \frac{1}{N}\#[h_{final}(x_i) \neq y_i]$ of the final hypothesis h_{final} is bounded above by

$$\epsilon \leq 2^T \prod_{t=1}^{T} \sqrt{\epsilon_t (1 - \epsilon_t)}.$$

Upper bound on total weight

$$
\begin{aligned}
\sum_{i=1}^{N} w_i^{t+1} &= \sum_{i=1}^{N} w_i^t \, \beta_t^{\left(1-|\, h_t(x_i)-y_i \,|\right)} \\
&\leq \sum_{i=1}^{N} w_i' \Big(1 - (1-\beta_t)(1 - |\, h_t(x_i) - y_i \,|)\Big) \\
&\leq \left(\sum_{i=1}^{N} w_i^t\right)\Big(1 - (1-\epsilon_t)\,(1-\beta_t)\Big).
\end{aligned}
$$

Combining over iterations

Combining the weight-update inequality over $t = 1, \ldots, T$, we get

$$\sum_{i=1}^{N} w_i^{T+1} \leq \prod_{t=1}^{T} \Big(1 - (1 - \epsilon_t)(1 - \beta_t) \Big). \tag{16}$$

Lower bound on total weight

The final hypothesis h_{final} makes a mistake on instance i only if

$$\prod_{t=1}^{T} \beta_t^{\left(1-|\,h_t(x_i)-y_i\,|\right)} \geq \left(\prod_{t=1}^{T} \beta_t\right)^{-\frac{1}{2}}. \tag{17}$$

The final weight of instance i is

$$w_i^{T+1} = D(i) \prod_{t=1}^{T} \beta_t^{\left(1-|\,h_t(x_i)-y_i\,|\right)}. \tag{18}$$

By comparing the sum of all final weights to those on examples where h_{final} is incorrect, one obtains

$$\sum_{i=1}^{N} w_i^{T+1} \geq \sum_{i:h_{final}(x_i)\neq y_i} w_i^{T+1} \geq e \left(\prod_{t=1}^{T} \beta_t\right)^{1/2},$$

where e is the error of h_{final}.

Resulting Error Bound

Combining (16) and the above,

$$e \leq \prod_{t=1}^{T} \frac{1-(1-\epsilon_t)(1-\beta_t)}{\sqrt{\beta_t}}. \tag{20}$$

Minimizing each factor leads to $\beta_t = \epsilon_t/(1-\epsilon_t)$. Plugging back yields

$$e \leq 2^T \prod_{t=1}^{T} \sqrt{\epsilon_t(1-\epsilon_t)},$$

Alternative forms of the bound

$$
\begin{aligned}
e &\leq \prod_{t=1}^{T} \sqrt{1 - 4\,\gamma_t^2} = \exp\Big(-\sum_{t=1}^{T} \mathrm{KL}\big(\tfrac{1}{2} \,\|\, \tfrac{1}{2} - \gamma_t\big)\Big) \\
&\leq \exp\Big(-2 \sum_{t=1}^{T} \gamma_t^2\Big).
\end{aligned}
$$

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- Weights assigned to examples.
- Upper bound on Potential: Edges of weak rules.

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- Weights assigned to Experts
- Upper bound on potential: Loss of alg.
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- Upper bound on Potential: Edges of weak rules.
- Lower bound on Potential: Error of majority vote.

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- Potential: An upper bound on the error. $\phi(x)$
- Weight: The gradient of the potential. $\nu = \frac{\partial}{\partial x}\phi(x)$