Improved Risk Tail Bounds for On-Line Algorithms *

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Abstract

We prove the strongest known bound for the risk of hypotheses selected from the ensemble generated by running a learning algorithm incrementally on the training data. Our result is based on proof techniques that are remarkably different from the standard risk analysis based on uniform convergence arguments.

1 Introduction

In this paper, we analyze the risk of hypotheses selected from the ensemble obtained by running an arbitrary on-line learning algorithm on an i.i.d. sequence of training data. We describe a procedure that selects from the ensemble a hypothesis whose risk is, with high probability, at most

$$M_n + O\left(\frac{(\ln n)^2}{n} + \sqrt{\frac{M_n}{n}\ln n}\right),$$

where M_n is the average cumulative loss incurred by the on-line algorithm on a training sequence of length n. Note that this bound exhibits the "fast" rate $(\ln n)^2/n$ whenever the cumulative loss nM_n is $O(1)$.

This result is proven through a refinement of techniques that we used in [2] to prove the substantially weaker bound $M_n + O\big(\sqrt{(\ln n)/n}\big)$. As in the proof of the older result, we analyze the empirical process associated with a run of the on-line learner using exponential inequalities for martingales. However, this time we control the large deviations of the on-line process using Bernstein's maximal inequality rather than the Azuma-Hoeffding inequality. This provides a much tighter bound on the average risk of the ensemble. Finally, we relate the risk of a specific hypothesis within the ensemble to the average risk. As in [2], we select this hypothesis using a deterministic sequential testing procedure, but the use of Bernstein's inequality makes the analysis of this procedure far more complicated.

The study of the statistical risk of hypotheses generated by on-line algorithms, initiated by Littlestone [5], uses tools that are sharply different from those used for uniform convergence analysis, a popular approach based on the manipulation of suprema of empirical

*Part of the results contained in this paper have been presented in a talk given at the NIPS 2004 workshop on "(Ab)Use of Bounds".

processes (see, e.g., [3]). Unlike uniform convergence, which is tailored to empirical risk minimization, our bounds hold for *any* learning algorithm. Indeed, disregarding efficiency issues, any learner can be run incrementally on a data sequence to generate an ensemble of hypotheses.

The consequences of this line of research to kernel and margin-based algorithms have been presented in our previous work [2].

Notation. An *example* is a pair (x, y), where $x \in \mathcal{X}$ (which we call *instance*) is a data element and $y \in \mathcal{Y}$ is the *label* associated with it. Instances x are tuples of numerical and/or symbolic attributes. Labels y belong to a finite set of symbols (the class elements) or to an interval of the real line, depending on whether the task is classification or regression. We allow a learning algorithm to output hypotheses of the form $h : \mathcal{X} \to \mathcal{D}$, where $\mathcal{D}$ is a decision space not necessarily equal to $\mathcal{Y}$. The goodness of hypothesis h on example (x, y) is measured by the quantity $\ell(h(x), y)$, where $\ell : \mathcal{D} \times \mathcal{Y} \to \mathbb{R}$ is a nonnegative and bounded *loss function*.

2 A bound on the average risk

An on-line algorithm A works in a sequence of trials. In each trial $t = 1, 2, \ldots$ the algorithm takes in input a hypothesis H_{t-1} and an example $Z_t = (X_t, Y_t)$, and returns a new hypothesis H_t to be used in the next trial. We follow the standard assumptions in statistical learning: the sequence of examples $Z^n = \big((X_1, Y_1), \ldots, (X_n, Y_n)\big)$ is drawn i.i.d. according to an unknown distribution over $\mathcal{X} \times \mathcal{Y}$. We also assume that the loss function ℓ satisfies $0 \le \ell \le 1$. The success of a hypothesis h is measured by the *risk* of h, denoted by $\mathtt{risk}(h)$. This is the expected loss of h on an example (X, Y) drawn from the underlying distribution, $\mathtt{risk}(h) = \mathbb{E}\,\ell(h(X), Y)$. Define also $\mathtt{risk}_{\mathtt{emp}}(h)$ to be the empirical risk of h on a sample Z^n,

$$\mathtt{risk}_{\mathtt{emp}}(h) = \frac{1}{n} \sum_{t=1}^{n} \ell(h(X_t), Y_t) \; .$$

Given a sample Z^n and an on-line algorithm A, we use $H_0, H_1, \ldots, H_{n-1}$ to denote the *ensemble of hypotheses generated by* A. Note that the ensemble is a function of the random training sample Z^n. Our bounds hinge on the sample statistic

$$M_n = M_n(Z^n) = \frac{1}{n} \sum_{t=1}^{n} \ell(H_{t-1}(X_t), Y_t)$$

which can be easily computed as the on-line algorithm is run on Z^n.

The following bound, a consequence of Bernstein's maximal inequality for martingales due to Freedman [4], is of primary importance for proving our results.

Lemma 1 *Let $L_1, L_2, \ldots$ be a sequence of random variables, $0 \le L_t \le 1$. Define the bounded martingale difference sequence $V_t = \mathbb{E}[L_t \mid L_1, \ldots, L_{t-1}] - L_t$ and the associated martingale $S_n = V_1 + \ldots + V_n$ with conditional variance $K_n = \sum_{t=1}^{n} \mathrm{Var}[L_t \mid L_1, \ldots, L_{t-1}]$. Then, for all $s, k \ge 0$,*

$$\mathbb{P}\left(S_n \ge s, K_n \le k\right) \le \exp\left(-\frac{s^2}{2k + 2s/3}\right) \; .$$

The next proposition, derived from Lemma 1, establishes a bound on the average risk of the ensemble of hypotheses.

Proposition 2 *Let $H_0, \ldots, H_{n-1}$ be the ensemble of hypotheses generated by an arbitrary on-line algorithm* $\mathtt{A}$*. Then, for any $0 < \delta \le 1$,*

$$\mathbb{P}\left(\frac{1}{n}\sum_{t=1}^{n}\mathtt{risk}(H_{t-1}) \ge M_n + \frac{36}{n}\ln\left(\frac{n\,M_n+3}{\delta}\right) + 2\sqrt{\frac{M_n}{n}\ln\left(\frac{n\,M_n+3}{\delta}\right)}\right) \le \delta\,.$$

The bound shown in Proposition 2 has the same rate as a bound recently proven by Zhang [6, Theorem 5]. However, rather than deriving the bound from Bernstein inequality as we do, Zhang uses an ad hoc argument.

Proof. Let

$$\mu_n = \frac{1}{n}\sum_{t=1}^{n}\mathtt{risk}(H_{t-1}) \quad \text{and} \quad V_{t-1} = \mathtt{risk}(H_{t-1}) - \ell(H_{t-1}(X_t), Y_t) \quad \text{for } t \ge 1.$$

Let κ_t be the conditional variance $\mathrm{Var}\big(\ell(H_{t-1}(X_t), Y_t) \mid Z_1, \ldots, Z_{t-1}\big)$. Also, set for brevity $K_n = \sum_{t=1}^n \kappa_t$, $K'_n = \lfloor \sum_{t=1}^n \kappa_t \rfloor$, and introduce the function $A(x) = 2\ln\frac{(x+1)(x+3)}{\delta}$ for $x \ge 0$. We find upper and lower bounds on the probability

$$\mathbb{P}\left(\sum_{t=1}^{n} V_{t-1} \ge A(K_n) + \sqrt{A(K_n)\,K_n}\right). \tag{1}$$

The upper bound is determined through a simple stratification argument over Lemma 1. We can write

$$\begin{aligned}
&\mathbb{P}\Big(\sum_{t=1}^{n} V_{t-1} \ge A(K_n) + \sqrt{A(K_n)\,K_n}\Big)\\
&\qquad\le \mathbb{P}\Big(\sum_{t=1}^{n} V_{t-1} \ge A(K'_n) + \sqrt{A(K'_n)\,K'_n}\Big)\\
&\qquad\le \sum_{s=0}^{n}\mathbb{P}\Big(\sum_{t=1}^{n} V_{t-1} \ge A(s) + \sqrt{A(s)\,s},\ K'_n = s\Big)\\
&\qquad\le \sum_{s=0}^{n}\mathbb{P}\Big(\sum_{t=1}^{n} V_{t-1} \ge A(s) + \sqrt{A(s)\,s},\ K_n \le s+1\Big)\\
&\qquad\le \sum_{s=0}^{n}\exp\Big(-\frac{(A(s)+\sqrt{A(s)\,s})^2}{\frac{2}{3}(A(s)+\sqrt{A(s)\,s}) + 2(s+1)}\Big) \quad \text{(using Lemma 1).}
\end{aligned}$$

Since $\frac{(A(s)+\sqrt{A(s)\,s})^2}{\frac{2}{3}\left(A(s)+\sqrt{A(s)\,s}\right)+2(s+1)} \ge A(s)/2$ for all $s \ge 0$, we obtain

$$(1) \le \sum_{s=0}^{n} e^{-A(s)/2} = \sum_{s=0}^{n}\frac{\delta}{(s+1)(s+3)} < \delta. \tag{2}$$

As far as the lower bound on (1) is concerned, we note that our assumption $0 \le \ell \le 1$ implies $\kappa_t \le \mathtt{risk}(H_{t-1})$ for all t which, in turn, gives $K_n \le n\mu_n$. Thus

$$\begin{aligned}
(1) &= \mathbb{P}\Big(n\mu_n - nM_n \ge A(K_n) + \sqrt{A(K_n)\,K_n}\Big)\\
&\ge \mathbb{P}\Big(n\mu_n - nM_n \ge A(n\mu_n) + \sqrt{A(n\mu_n)\,n\mu_n}\Big)\\
&= \mathbb{P}\Big(2n\mu_n \ge 2nM_n + 3A(n\mu_n) + \sqrt{4n\,M_n\,A(n\mu_n) + 5A(n\mu_n)^2}\Big)\\
&= \mathbb{P}\Big(x \ge B + \tfrac{3}{2}A(x) + \sqrt{B\,A(x) + \tfrac{5}{4}A^2(x)}\Big),
\end{aligned}$$

where we set for brevity $x = n\mu_n$ and $B = n\, M_n$. We would like to solve the inequality

$$x \geq B + \tfrac{3}{2}A(x) + \sqrt{B\,A(x) + \tfrac{5}{4}A^2(x)} \tag{3}$$

w.r.t. x. More precisely, we would like to find a suitable upper bound on the (unique) x^* such that the above is satisfied as an equality.

A (tedious) derivative argument along with the upper bound $A(x) \leq 4\, \ln\left(\frac{x+3}{\delta}\right)$ show that

$$x' = B + 2\sqrt{B\, \ln\left(\tfrac{B+3}{\delta}\right)} + 36 \ln\left(\tfrac{B+3}{\delta}\right)$$

makes the left-hand side of (3) larger than its right-hand side. Thus x' is an upper bound on x^*, and we conclude that

$$(1) \geq \mathbb{P}\Big(x \geq B + 2\sqrt{B\, \ln\left(\tfrac{B+3}{\delta}\right)} + 36 \ln\left(\tfrac{B+3}{\delta}\right)\Big)$$

which, recalling the definitions of x and B, and combining with (2), proves the bound. □

3 Selecting a good hypothesis from the ensemble

If the decision space $\mathcal{D}$ of A is a convex set and the loss function ℓ is convex in its first argument, then via Jensen's inequality we can directly apply the bound of Proposition 2 to the risk of the *average hypothesis* $\overline{H} = \frac{1}{n}\sum_{t=1}^{n} H_{t-1}$. This yields

$$\mathbb{P}\left(\mathtt{risk}(\overline{H}) \geq M_n + \frac{36}{n}\, \ln\left(\frac{n\, M_n + 3}{\delta}\right) + 2\sqrt{\frac{M_n}{n}\, \ln\left(\frac{n\, M_n + 3}{\delta}\right)}\right) \leq \delta\,. \tag{4}$$

Observe that this is a $O(1/n)$ bound whenever the cumulative loss $n\, M_n$ is $O(1)$.

If the convexity hypotheses do not hold (as in the case of classification problems), then the bound in (4) applies to a hypothesis randomly drawn from the ensemble (this was investigated in [1] though with different goals).

In this section we show how to deterministically pick from the ensemble a hypothesis whose risk is close to the average ensemble risk.

To see how this could be done, let us first introduce the functions

$$\mathcal{E}_\delta(r,t) = \frac{8B}{3(n-t)} + \sqrt{\frac{2Br}{n-t}} \qquad \text{and} \qquad c_\delta(r,t) = \mathcal{E}_\delta\left(r + \sqrt{\frac{2Br}{n-t}}, t\right),$$

with $B = \ln \frac{n(n+2)}{\delta}$.

Let $\mathtt{risk}_{\mathtt{emp}}(H_t, t+1) + \mathcal{E}_\delta\big(\mathtt{risk}_{\mathtt{emp}}(H_t, t+1), t\big)$ be the *penalized empirical risk* of hypothesis H_t, where

$$\mathtt{risk}_{\mathtt{emp}}(H_t, t+1) = \frac{1}{n-t}\sum_{i=t+1}^{n} \ell(H_t(X_i), Y_i)$$

is the empirical risk of H_t on the remaining sample $Z_{t+1}, \ldots, Z_n$. We now analyze the performance of the learning algorithm that returns the hypothesis $\widehat{H}$ minimizing the penalized risk estimate over all hypotheses in the ensemble, i.e., [1]

$$\widehat{H} = \operatorname*{argmin}_{0 \leq t < n}\Big(\mathtt{risk}_{\mathtt{emp}}(H_t, t+1) + \mathcal{E}_\delta\big(\mathtt{risk}_{\mathtt{emp}}(H_t, t+1), t\big)\Big)\,. \tag{5}$$

[1] Note that, from an algorithmic point of view, this hypothesis is fairly easy to compute. In particular, if the underlying on-line algorithm is a standard kernel-based algorithm, $\widehat{H}$ can be calculated via a single sweep through the example sequence.

Lemma 3 *Let $H_0, \ldots, H_{n-1}$ be the ensemble of hypotheses generated by an arbitrary online algorithm* $\mathtt{A}$ *working with a loss ℓ satisfying $0 \le \ell \le 1$. Then, for any $0 < \delta \le 1$, the hypothesis $\widehat{H}$ satisfies*

$$\mathbb{P}\left(\mathtt{risk}(\widehat{H}) > \min_{0 \le t < n}\big(\mathtt{risk}(H_t) + 2\,c_\delta(\mathtt{risk}(H_t), t)\big)\right) \le \delta\,.$$

Proof. We introduce the following short-hand notation

$$\begin{aligned} R_t &= \mathtt{risk}_{\mathtt{emp}}(H_t, t+1), \qquad \widehat{T} = \operatorname*{argmin}_{0 \le t < n}\,(R_t + \mathcal{E}_\delta(R_t, t)) \\ T^* &= \operatorname*{argmin}_{0 \le t < n}\,(\mathtt{risk}(H_t) + 2c_\delta(\mathtt{risk}(H_t), t))\ . \end{aligned}$$

Also, let $H^* = H_{T^*}$ and $R^* = \mathtt{risk}_{\mathtt{emp}}(H_{T^*}, T^* + 1) = R_{T^*}$. Note that $\widehat{H}$ defined in (5) coincides with $H_{\widehat{T}}$. Finally, let

$$Q(r,t) = \frac{\sqrt{2B(2B + 9r(n-t))} - 2B}{3(n-t)}\ .$$

With this notation we can write

$$\begin{aligned} &\mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta(\mathtt{risk}(H^*), T^*)\Big) \\ &\quad\le\ \mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta\big(R^* - Q(R^*, T^*), T^*\big)\Big) \\ &\quad\ +\ \mathbb{P}\Big(\mathtt{risk}(H^*) < R^* - Q(R^*, T^*)\Big) \\ &\quad\le\ \mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta\left(R^* - Q(R^*, T^*), T^*\right)\Big) \\ &\quad\ +\ \sum_{t=0}^{n-1}\mathbb{P}\Big(\mathtt{risk}(H_t) < R_t - Q(R_t, t)\Big)\ . \end{aligned}$$

Applying the standard Bernstein's inequality (see, e.g., [3, Ch. 8]) to the random variables R_t with $|R_t| \le 1$ and expected value $\mathtt{risk}(H_t)$, and upper bounding the variance of R_t with $\mathtt{risk}(H_t)$, yields

$$\mathbb{P}\left(\mathtt{risk}(H_t) < R_t - \frac{B + \sqrt{B(B + 18(n-t)\mathtt{risk}(H_t))}}{3(n-t)}\right) \le e^{-B}\ .$$

With a little algebra, it is easy to show that

$$\mathtt{risk}(H_t) < R_t - \frac{B + \sqrt{B(B + 18(n-t)\mathtt{risk}(H_t))}}{3(n-t)}$$

is equivalent to $\mathtt{risk}(H_t) < R_t - Q(R_t, t)$. Hence, we get

$$\begin{aligned} &\mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta(\mathtt{risk}(H^*), T^*)\Big) \\ &\quad\le\ \mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta\left(R^* - Q(R^*, T^*), T^*\right)\Big) + n\,e^{-B} \\ &\quad\le\ \mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2\mathcal{E}_\delta(R^*, T^*)\Big) + n\,e^{-B} \end{aligned}$$

where in the last step we used

$$Q(r,t) \le \sqrt{\frac{2Br}{n-t}} \qquad \text{and} \qquad c_\delta\left(r - \sqrt{\frac{2Br}{n-t}}, t\right) = \mathcal{E}_\delta(r,t)\,.$$

Set for brevity $\mathcal{E} = \mathcal{E}_\delta(R^*, T^*)$. We have

$$\begin{aligned}
&\mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big) \\
&= \mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2\mathcal{E},\, R_{\widehat{T}} + \mathcal{E}_\delta(R_{\widehat{T}}, \widehat{T}) \le R^* + \mathcal{E}\Big) \\
&\qquad \text{(since } R_{\widehat{T}} + \mathcal{E}_\delta(R_{\widehat{T}}, \widehat{T}) \le R^* + \mathcal{E} \text{ holds with certainty)} \\
&\le \sum_{t=0}^{n-1} \mathbb{P}\Big(R_t + \mathcal{E}_\delta(R_t, t) \le R^* + \mathcal{E},\, \mathtt{risk}(H_t) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big)\,. \qquad (6)
\end{aligned}$$

Now, if $R_t + \mathcal{E}_\delta(R_t, t) \le R^* + \mathcal{E}$ holds, then at least one of the following three conditions $R_t \le \mathtt{risk}(H_t) - \mathcal{E}_\delta(R_t, t), \quad R^* > \mathtt{risk}(H^*) + \mathcal{E}, \quad \mathtt{risk}(H_t) - \mathtt{risk}(H^*) < 2\mathcal{E}$ must hold. Hence, for any fixed t we can write

$$\begin{aligned}
&\mathbb{P}\Big(R_t + \mathcal{E}_\delta(R_t, t) \le R^* + \mathcal{E},\, \mathtt{risk}(H_t) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big) \\
&\le \mathbb{P}\Big(R_t \le \mathtt{risk}(H_t) - \mathcal{E}_\delta(R_t, t),\, \mathtt{risk}(H_t) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big) \\
&\qquad + \mathbb{P}\Big(R^* > \mathtt{risk}(H^*) + \mathcal{E},\, \mathtt{risk}(H_t) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big) \\
&\qquad + \mathbb{P}\Big(\mathtt{risk}(H_t) - \mathtt{risk}(H^*) < 2\,\mathcal{E},\, \mathtt{risk}(H_t) > \mathtt{risk}(H^*) + 2\mathcal{E}\Big) \\
&\le \mathbb{P}\Big(R_t \le \mathtt{risk}(H_t) - \mathcal{E}_\delta(R_t, t)\Big) + \mathbb{P}\Big(R^* > \mathtt{risk}(H^*) + \mathcal{E}\Big)\,. \qquad (7)
\end{aligned}$$

Plugging (7) into (6) we have

$$\begin{aligned}
&\mathbb{P}\left(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2\mathcal{E}\right) \\
&\le \sum_{t=0}^{n-1} \mathbb{P}\Big(R_t \le \mathtt{risk}(H_t) - \mathcal{E}_\delta(R_t, t)\Big) + n\,\mathbb{P}\Big(R^* > \mathtt{risk}(H^*) + \mathcal{E}\Big) \\
&\le n\,e^{-B} + n \sum_{t=0}^{n-1} \mathbb{P}\Big(R_t \ge \mathtt{risk}(H_t) + \mathcal{E}_\delta(R_t, t)\Big) \;\le\; n\,e^{-B} + n^2\,e^{-B},
\end{aligned}$$

where in the last two inequalities we applied again Bernstein's inequality to the random variables R_t with mean $\mathtt{risk}(H_t)$. Putting together we obtain

$$\mathbb{P}\big(\mathtt{risk}(\widehat{H}) > \mathtt{risk}(H^*) + 2c_\delta(\mathtt{risk}(H^*), T^*)\big) \le (2n + n^2)e^{-B}$$

which, recalling that $B = \ln \frac{n(n+2)}{\delta}$, implies the thesis. □

Fix $n \ge 1$ and $\delta \in (0,1)$. For each $t = 0, \ldots, n-1$, introduce the function

$$f_t(x) = x + \frac{11C}{3}\,\frac{\ln(n-t) + 1}{n-t} + 2\sqrt{\frac{2Cx}{n-t}}, \qquad x \ge 0,$$

where $C = \ln \frac{2n(n+2)}{\delta}$. Note that each f_t is monotonically increasing. We are now ready to state and prove the main result of this paper.

Theorem 4 *Fix any loss function ℓ satisfying $0 \le \ell \le 1$. Let $H_0, \ldots, H_{n-1}$ be the ensemble of hypotheses generated by an arbitrary on-line algorithm* $\mathtt{A}$ *and let $\widehat{H}$ be the hypothesis minimizing the penalized empirical risk expression obtained by replacing c_δ with $c_{\delta/2}$ in (5). Then, for any $0 < \delta \le 1$, $\widehat{H}$ satisfies*

$$\mathbb{P}\left(\mathtt{risk}(\widehat{H}) \ge \min_{0 \le t < n} f_t\left(M_{t,n} + \frac{36}{n-t}\ln\frac{2n(n+3)}{\delta} + 2\sqrt{\frac{M_{t,n}\ln\frac{2n(n+3)}{\delta}}{n-t}}\right)\right) \le \delta,$$

where $M_{t,n} = \frac{1}{n-t}\sum_{i=t+1}^{n} \ell(H_{i-1}(X_i), Y_i)$. In particular, upper bounding the minimum over t with $t = 0$ yields

$$\mathbb{P}\left(\mathtt{risk}(\widehat{H}) \ge f_0\left(M_n + \frac{36}{n}\ln\frac{2n(n+3)}{\delta} + 2\sqrt{\frac{M_n \ln\frac{2n(n+3)}{\delta}}{n}}\right)\right) \le \delta\,. \tag{8}$$

For $n \to \infty$, bound (8) shows that $\mathtt{risk}(\widehat{H})$ is bounded with high probability by

$$M_n + O\left(\frac{\ln^2 n}{n} + \sqrt{\frac{M_n \ln n}{n}}\right)\,.$$

If the empirical cumulative loss $n\,M_n$ is small (say, $M_n \le c/n$, where c is constant with n), then our penalized empirical risk minimizer $\widehat{H}$ achieves a $O\big((\ln^2 n)/n\big)$ risk bound. Also, recall that, in this case, under convexity assumptions the average hypothesis $\overline{H}$ achieves the sharper bound $O(1/n)$.

Proof. Let $\mu_{t,n} = \frac{1}{n-t}\sum_{i=t}^{n-1} \mathtt{risk}(H_i)$. Applying Lemma 3 with $c_{\delta/2}$ we obtain

$$\mathbb{P}\Big(\mathtt{risk}(\widehat{H}) > \min_{0 \le t < n}\big(\mathtt{risk}(H_t) + c_{\delta/2}(\mathtt{risk}(H_t), t)\big)\Big) \le \frac{\delta}{2}\,. \tag{9}$$

We then observe that

$$\begin{aligned}
&\min_{0 \le t < n}\Big(\mathtt{risk}(H_t) + c_{\delta/2}(\mathtt{risk}(H_t), t)\Big) \\
&= \min_{0 \le t < n}\min_{t \le i < n}\Big(\mathtt{risk}(H_i) + c_{\delta/2}(\mathtt{risk}(H_i), i)\Big) \\
&\le \min_{0 \le t < n}\frac{1}{n-t}\sum_{i=t}^{n-1}\Big(\mathtt{risk}(H_i) + c_{\delta/2}(\mathtt{risk}(H_i), i)\Big) \\
&\le \min_{0 \le t < n}\left(\mu_{t,n} + \frac{1}{n-t}\sum_{i=t}^{n-1}\frac{8}{3}\frac{C}{n-i} + \frac{1}{n-t}\sum_{i=t}^{n-1}\left(\sqrt{\frac{2C\,\mathtt{risk}(H_i)}{n-i}} + \frac{C}{n-i}\right)\right) \\
&\qquad \text{(using the inequality } \sqrt{x+y} \le \sqrt{x} + \tfrac{y}{2\sqrt{x}}\text{)} \\
&= \min_{0 \le t < n}\left(\mu_{t,n} + \frac{1}{n-t}\sum_{i=t}^{n-1}\frac{11}{3}\frac{C}{n-i} + \frac{1}{n-t}\sum_{i=t}^{n-1}\sqrt{\frac{2C\,\mathtt{risk}(H_i)}{n-i}}\right) \\
&\le \min_{0 \le t < n}\left(\mu_{t,n} + \frac{11C}{3}\frac{\ln(n-t)+1}{n-t} + 2\sqrt{\frac{2C\mu_{t,n}}{n-t}}\right) \\
&\qquad \text{(using } \textstyle\sum_{i=1}^{k} 1/i \le 1 + \ln k \text{ and the concavity of the square root)} \\
&= \min_{0 \le t < n} f_t(\mu_{t,n})\,.
\end{aligned}$$

Now, it is clear that Proposition 2 can be immediately generalized to imply the following set of inequalities, one for each $t = 0, \dots, n-1$,

$$\mathbb{P}\left(\mu_{t,n} \geq M_{t,n} + \frac{36\,A}{n-t} + 2\sqrt{\frac{M_{t,n}\,A}{n-t}}\right) \leq \frac{\delta}{2n} \tag{10}$$

where $A = \ln \frac{2n(n+3)}{\delta}$. Introduce the random variables $K_0, \dots, K_{n-1}$ to be defined later. We can write

$$\mathbb{P}\left(\min_{0 \leq t < n}\Big(\texttt{risk}(H_t) + c_{\delta/2}(\texttt{risk}(H_t), t)\Big) \geq \min_{0 \leq t < n} K_t\right)$$
$$\leq \mathbb{P}\left(\min_{0 \leq t < n} f_t(\mu_{t,n}) \geq \min_{0 \leq t < n} K_t\right) \leq \sum_{t=0}^{n-1} \mathbb{P}\left(f_t(\mu_{t,n}) \geq K_t\right) .$$

Now, for each $t = 0, \dots, n-1$, define $K_t = f_t\left(M_{t,n} + \frac{36\,A}{n-t} + 2\sqrt{\frac{M_{t,n}\,A}{n-t}}\right)$. Then (10) and the monotonicity of $f_0, \dots, f_{n-1}$ allow us to obtain

$$\mathbb{P}\left(\min_{0 \leq t < n}\Big(\texttt{risk}(H_t) + c_{\delta/2}(\texttt{risk}(H_t), t)\Big) \geq \min_{0 \leq t < n} K_t\right)$$
$$\leq \sum_{t=0}^{n-1} \mathbb{P}\left(f_t(\mu_{t,n}) \geq f_t\left(M_{t,n} + \frac{36\,A}{n-t} + 2\sqrt{\frac{M_{t,n}\,A}{n-t}}\right)\right)$$
$$= \sum_{t=0}^{n-1} \mathbb{P}\left(\mu_{t,n} \geq M_{t,n} + \frac{36\,A}{n-t} + 2\sqrt{\frac{M_{t,n}\,A}{n-t}}\right) \leq \delta/2 .$$

Combining with (9) concludes the proof. □

4 Conclusions and current research issues

We have shown tail risk bounds for specific hypotheses selected from the ensemble generated by the run of an arbitrary on-line algorithm. Proposition 2, our simplest bound, is proven via an easy application of Bernstein's maximal inequality for martingales, a quite basic result in probability theory. The analysis of Theorem 4 is also centered on the same martingale inequality. An open problem is to simplify this analysis, possibly obtaining a more readable bound. Also, the bound shown in Theorem 4 contains $\ln n$ terms. We do not know whether these logarithmic terms can be improved to $\ln(M_n n)$, similarly to Proposition 2. A further open problem is to prove lower bounds, even in the special case when nM_n is bounded by a constant.

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