# Sorting and Searching With a Faulty Comparison Oracle 

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#### Abstract

We study sorting and searching using a comparison oracle that "lies." First, we prove that an algorithm of Rivest, Meyer, Kleitman, Winklmann and Spencer for searching in an $n$-element list using a comparison oracle that lies $E$ times requires at most $O(\log n+E)$ comparisons, improving the best previously known bound of $\log n+E \log \log n+O(E \log E)$. A lower bound, easily obtained from their results, establishes that the number of comparisons used by their algorithm is within a constant factor of optimal.

We apply their search algorithm to obtain an algorithm for sorting an $n$ element list with $E$ lies that requires at most $O(n \log n+E n)$ comparisons, improving on the algorithm of Lakshmanan, Ravikumar and Ganesan, which required at most $O\left(n \log n+E n+E^{2}\right)$ comparisons. A lower bound proved by Lakshmanan, Ravikumar and Ganesan establishes that the number of comparisons used by our sorting algorithm is optimal to within a constant factor.


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## 1 Introduction

Rivest, Meyer, Kleitman, Winklmann, and Spencer [RMK ${ }^{+} 80$ ] described an algorithm for finding an element $k$ in $\{1, \ldots, n\}$ using questions of the form "is $k \leq a$ ?" for $a$ chosen by the algorithm, when up to $E$ of their algorithm's questions were answered incorrectly. They showed that the algorithm was guaranteed to output $k$, and that their algorithm used at most ${ }^{1}$

$$
\log n+E \log \log n+O(E \log E)
$$

comparisons. In this note, we show that the number of comparisons required by their algorithm is at most

$$
O(\log n+E)
$$

improving on their bound when $E$ grows faster than $(\log n) /(\log \log n)$.
A trivial application of their results provides a lower bound of $\Omega(\log n+E)$, establishing that their algorithm is optimal to within a constant factor.

We may easily apply this searching bound to show that an insertion sort algorithm, which uses their algorithm is a subroutine to determine where each insertion is to take place, requires at most $O(n \log n+E n)$ comparisons to sort $n$ keys with $E$ "lies," improving on the bound of $O\left(n \log n+E n+E^{2}\right)$ proved by Lakshmanan, Ravikumar and Ganesan [LRG91] for a closely related algorithm when $E$ grows faster than $n$. A lower bound of $\Omega(n \log n+E n)$ comparisons proved in that paper establishes the fact that our modification of their algorithm is within a constant factor of optimal.

The $\left[\mathrm{RMK}^{+} 80\right]$ paper contained a detailed proof of the following theorem, which is the starting point of our analysis. ${ }^{2}$

Theorem 1 ([RMK ${ }^{+80]): ~ F o r ~ a n y ~ n o n n e g a t i v e ~ i n t e g e r ~} E$ and positive integer n, let $Q(n, E)$ denote the number of comparison questions necessary in the worst case to identify an unknown $k \in\{1, \ldots, n\}$ when up to $E$ of the questions may receive an erroneous answer. Then

$$
\min \left\{u: 2^{u} \geq n \sum_{i=0}^{E}\binom{u}{i}\right\} \leq Q(n, E) \leq \min \left\{u: 2^{u-E} \geq n \sum_{i=0}^{E}\binom{u-E}{i}\right\} .
$$

Our improvement on their upper bound is obtained by applying an unusual approximation to $\sum_{i=0}^{d}\binom{m}{i}$. It is a a direct consequence of Hoeffding's inequality, a bound on the probability that the following two quantities differ by much:

- The probability that a (biased) coin will come up heads,
- The fraction of the time it comes up heads when flipped $m$ times.

Their approximation improves on the usual approximation of $(\epsilon \mathrm{m} / \mathrm{d})^{d}$ [BEHW89] when $d$ is large relative to $m$, which is useful for this application.

Note that if $E \in \Omega(\log n)$, the $E n$ term in our sorting bound of $O(n \log n+E n)$ dominates. This is especially interesting in light of the result of Ravikumar, Ganesan and Lakshmanan [RGL87], which says that $(E+1) n-1$ comparisons are necessary and

[^1]sufficient to simply find the maximum of $n$ elements using a comparison oracle that lies $E$ times. Thus, if $E \in \Omega(\log n)$, only a constant factor more comparisons are required to sort $n$ elements than to simply output their maximum. It is also perhaps worth repeating the observation in [LRG91] that any $O(n \log n)$ sorting algorithm can be trivially modified to cope with $E$ lies by repeating each comparison $2 E+1$ times, obtaining an algorithm that uses $O(E n \log n)$ comparisons. Thus, for moderately large $E$, our sorting result can be viewed as knocking off a log factor from what can be obtained trivially.

For those familiar with the Computational Learning Theory literature, as noted by Goldman, Rivest and Schapire [GRS89], another interpretation of the sorting problem is as the problem of learning a total order on $n$ elements using Angluin's "membership queries" [Ang88]. Our sorting result can therefore be interpreted as determining (to within a constant factor) the number of membership queries required for learning a total order, when a bounded number of the membership queries are answered incorrectly.

In addition to the aforementioned previous work, sorting and searching with a faulty comparison oracle has been studied under at least two other assumptions about the generation of the faults, including that they are generated independently at random [Pel89, FPRU90], and that there is a constant $r$ such that for each $i$, at most $i r$ of the first $i$ comparisons are answered incorrectly [Pe189, AD91].

## 2 Approximating $\sum_{i=0}^{d}\binom{m}{i}$

In this section, we state and, for completeness, prove, a useful approximation to $\sum_{i=0}^{d}\binom{m}{i}$.

The following form of the Hoeffding bounds will be useful.
Theorem 2 (c.f., [Pol84]): Let $Y_{1}, \ldots, Y_{m}$ be independent, identically distributed $\{0,1\}$ valued random variables such that for each $i, \operatorname{Pr}\left(Y_{i}=1\right)=p$. Then, for any $\alpha \geq 0$,

$$
\operatorname{Pr}\left(\frac{1}{m} \sum_{i=1}^{m} Y_{i} \leq p-\alpha\right) \leq e^{-2 \alpha^{2} m}
$$

The following Corollary is the useful approximation.
Corollary 3: Choose $d, m \in \mathbf{N}, d \leq m / 2$. Then

$$
\sum_{i=0}^{d}\binom{m}{i} \leq 2^{m} \exp \left(\frac{-(m-2 d)^{2}}{2 m}\right)
$$

Proof: Since if an unbiased coin is flipped independently $m$ times (call the results of the flips $Y_{1}, \ldots, Y_{m}$ ), any subset of the $m$ tosses is equally likely to be the set of trials in which heads appeared,

$$
\frac{1}{2^{m}} \sum_{i=0}^{d}\binom{m}{i}=\operatorname{Pr}\left(\frac{1}{m} \sum_{i=0}^{m} Y_{i} \leq \frac{d}{m}\right) \leq \exp \left(-2(1 / 2-d / m)^{2} m\right),
$$

applying Theorem 2 with $p=1 / 2$. Multiplying both sides by $2^{m}$ and simplifying yields the desired result.

## 3 Searching with a faulty comparison oracle

In the section, we present our main result.
Theorem 4: For any nonnegative integer $E$ and positive integer $n$, let $Q(n, E)$ denote the number of comparison questions necessary in the worst case to identify an unknown $k \in\{1, \ldots, n\}$ when up to $E$ of the questions may receive an erroneous answer. Then

$$
Q(n, E)=O(\log n+E)
$$

Proof: First, note that

$$
\min \left\{u: 2^{u-E} \geq n \sum_{i=0}^{E}\binom{u-E}{i}\right\} \leq \min \left\{u: 2^{u} \geq n \sum_{i=0}^{E}\binom{u}{i}\right\}+E .
$$

Thus, by Theorem 1, a bound of $u+E$ holds for any $u$ such that

$$
2^{u} \geq n \sum_{i=0}^{E}\binom{u}{i} .
$$

Fix $E$ and $n$. Let

$$
\begin{equation*}
u=\lceil 4 \max \{2 \ln n, E\}\rceil . \tag{3.1}
\end{equation*}
$$

In particular,

$$
\begin{aligned}
u & \geq 8 \ln n \\
\sqrt{u} & \geq 2 \sqrt{2 \ln n} \\
u & \geq 2 \sqrt{2 u \ln n} .
\end{aligned}
$$

Returning to (3.1), we may obtain the following sequence of inequalities,

$$
\begin{aligned}
u & \geq 2 \max \{\sqrt{2 u \ln n}, 2 E\} \\
u & \geq \sqrt{2 u \ln n}+2 E \\
u-2 E & \geq \sqrt{2 u \ln n} \\
(u-2 E)^{2} & \geq 2 u \ln n \\
\frac{(u-2 E)^{2}}{2 u} & \geq \ln n \\
\exp \left(\frac{(u-2 E)^{2}}{2 u}\right) & \geq n \\
\exp \left(\frac{-(u-2 E)^{2}}{2 u}\right) & \leq 1 / n
\end{aligned}
$$

Applying Corollary 3, we obtain

$$
\begin{aligned}
\frac{1}{2^{u}} \sum_{i=0}^{E}\binom{u}{i} & \leq 1 / n \\
n \sum_{i=0}^{E}\binom{u}{i} & \leq 2^{u}
\end{aligned}
$$

Applying Theorem 1, this implies that the number of comparisons used by their algorithm is at most

$$
\begin{aligned}
u+E & =\lceil 4 \max \{2 \ln n, E\}\rceil+E \\
& \leq 8 \ln n+5 E+1
\end{aligned}
$$

completing the proof.
Next, we turn to lower bounds.
Theorem 5: For any nonnegative integer $E$ and positive integer $n \geq 2$, let $Q(n, E)$ denote the number of comparison questions necessary in the worst case to identify an unknown $k \in\{1, \ldots, n\}$ when up to $E$ of the questions may receive an erroneous answer. Then

$$
Q(n, E)=\Omega(\log n+E)
$$

Proof: Fix $E$ and $n$. Note that

$$
2^{u}-n \sum_{i=0}^{E}\binom{u}{i}
$$

is an increasing function of $u$, and therefore, by Theorem 1 that any $u$ for which

$$
2^{u}<n \sum_{i=0}^{E}\binom{u}{i}
$$

provides a lower bound on $Q(n, E)$. Let $u=\lfloor\log n\rfloor+E$. Then

$$
\begin{aligned}
2^{u} & \leq n 2^{E} \\
& =n \sum_{i=0}^{E}\binom{E}{i} \\
& <n \sum_{i=0}^{E}\binom{\lfloor\log n\rfloor+E}{i} \quad(\text { since } n \geq 2) \\
& =n \sum_{i=0}^{E}\binom{u}{i} .
\end{aligned}
$$

This completes the proof.

## 4 Sorting with a faulty comparison oracle

In this section, we describe how to apply the algorithm of the previous section to obtain a sorting algorithm that copes with incorrect answers to comparison questions, and requires a number of comparisons that is within a constant factor of optimal.

We begin by describing a modification of binary insertion sort that uses the robust binary search algorithm of $\left[\mathrm{RMK}^{+} 80\right]$ to determine where to insert. Pseudo-code for this algorithm is given in Figure 4.1.

The following follows trivially from the results of the previous section.

```
algorithm robust-insertion-sort ( \(A, E, n\) )
array \(A ;(n\) elements in \(A\) )
integer \(E\);
integer \(n\) :
for \(i=2\) to \(n\)
    begin
            use \(\left[\mathrm{RMK}^{+} 80\right]\) to determine where \(A[i]\) should be
                inserted in \(A[1], \ldots, A[i-1]\), assuming at most \(E\) lies
                (during this search), say it is before \(A[k]\);
            insert \(A[i]\) before \(A[k]\);
    end;
```

Figure 4.1: Pseudo-code for a robust sorting algorithm.

Theorem 6: The algorithm robust-insertion-sort correctly sorts an array of $n$ elements when at most $E$ of its comparison questions are answered incorrectly, using

$$
O(n \log n+E n)
$$

comparisons.
The following theorem, due to Lakshmanan, Ravikumar and Ganesan, establishes that the number of comparisons used by robust-insertion-sort is within a constant factor of optimal.

Theorem 7 ([LRG91]): Any correct algorithm for sorting $n$ keys, when up to E comparisons may be answered incorrectly, must make

$$
\Omega(n \log n)+E(n-1)
$$

comparisons.

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[^1]:    ${ }^{1}$ In this paper, we follow usual convention of denoting the base 2 logarithm by $\log$ and the natural logarithm by ln.
    ${ }^{2}$ Bounds of $O(\log n+E)$ on the first minimum of this theorem were obtained independently by CesaBianchi and Warmuth [CW92] while working on another application.

