Toward a Better Understanding of Leaderboard

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Abstract

The leaderboard in machine learning competitions is a tool to show the performance of various participants and to compare them. However, the leaderboard quickly becomes no longer accurate, due to hack or overfitting. This article gives two pieces of advice to prevent easy hack or overfitting. By following these advice, we reach the conclusion that something like the Ladder leaderboard introduced in [1] is inevitable. With this understanding, we naturally simplify Ladder by eliminating its redundant computation and explain how to choose the parameter and interpret it. We also prove that the sample complexity is cubic to the desired precision of the leaderboard.

1 Introduction

Machine learning competitions have been a popular platform for young students to practice their knowledge, for scientists to apply their expertise, and for industries to solve their data mining problems. For instance, the Internet streaming media company Netflix held the Netflix Prize competition in 2006, to find a better program to predict user preferences. Kaggle, an online platform, hosts regularly competitions since 2010.

These competitions are usually prediction problems. The participant is given the independent variable \( X \), and then he is required to predict the dependent variable \( Y \). Usually, the host divides his data into three data sets: \textit{training}, \textit{validation} and \textit{test}. The training dataset is fully available: every participant (having a competition account) can download it and observe its \( Y \) as well as its \( X \). This allows them to build their models. The validation data set is partially available to participants: they can only observe its \( X \). This dataset is used to construct the so-called leaderboard. The participants submit their prediction of \( Y \) to the host, and the host calculates their scores and ranks, and show them on the leaderboard, so that every participant could know his chance to win the competition. The test dataset is private. They are only used once at the final day to determine who is the final winner. Usually, the winner gets a reward.

The reason that the final result is determined by the reserved test set instead of the validation set is because the validation set could be hacked. Since the participant could submit his prediction over and over during the life of the competition, he has much chance to improve his model’s performance on the validation set, either by overfitting or hacking. In consequence, by the final day, the score he gets on the validation set may have been much higher than his model deserves. This is why it is frequently observed that the final winner of the competition is not the “winner” on the leaderboard.

Although the leaderboard has no effect on the decision of the final winner, it could be quite annoying if it cannot truly reflect the performance of each participant. Firstly, such a leaderboard allures inexperienced participants to overfit the validation set. Secondly, it encourages certain participants to hack the validation set in order to get a fake temporary honor or to disturb the order of the competition. Thirdly, it is not a good experience to see one’s non-overfitting model rank below someone hacking the validation set. It could be said that during the whole life of the competition, the participants compete around the leaderboard.

In view of this, some researchers tried to build an accurate leaderboard by preserving the accuracy of the estimator of the loss function. This could be hard since the participant can modify their model...
adaptively according to the feedback they get from the leaderboard. [2, 3] suggest that maintaining accurate estimates on a sequence of many adaptively chosen classifiers may be computationally intractable. In light of this, [1] proposes the Ladder mechanism to restrain the feedback that the participant could get from the leaderboard. The idea is that the participant gets a score if and only if this score is higher than the best among the past by some margin. By restraining the feedback, the participants have less information to adapt their models, and thus less chance to hack the leaderboard by overfitting the validation set.

However, [1] fails to point out whether this kind of mechanism is necessary: does there exist any other mechanism that achieves the same or better effect? If we have to use Ladder, what is its strength and shortcoming? How well can we hack the leaderboard? Is it true that the first leader is better than the second? If so, then by how much? There are two parameters in Ladder: margin \( \eta \) and precision \( \eta \); what is their relationship? Does the heuristic way to choose \( \eta \) provided in the paper have any theoretic guarantee? If the participant holds many accounts, is Ladder still effective?

In our paper, we answer these questions. A better understanding of the leaderboard will be achieved during the reading of this article. First, we show that traditional leaderboard is easy to hack. In consequence, something like Ladder mechanism is necessary. Then, we perform another hack to show that a leaderboard cannot be arbitrarily accurate (Section 2). Afterwards, we recognize the essence inside the Ladder mechanism and thus simplify it (Section 3). Finally, we generalize the Theorem 3.1 in [1] to take into consideration of the fact that each participant may be allowed to possess multiple accounts. And we slightly improve the upper bound as well (by eliminating the dependence on \( n \) in the logarithmic factor). Our result shows that, while using Ladder mechanism, the leaderboard needs \( \tilde{O}(M \epsilon^{-3}) \) samples to control the error within \( \epsilon \), where \( M \) is the number of accounts. This result suggests that Ladder is relatively robust to number of submissions, but may still be vulnerable to number of accounts (Section 4). In this article, we study the binary classification competition, but our result can be straightforwardly generalized to other kinds of competitions.

The highlight of this article is that we are not advertising any “magic” algorithm; we are just pursuing a better understanding of the leaderboard. We depart from some basic property (robust against hacks and overfittings) that a leaderboard should satisfy in order to protect its accuracy and fairness. We reach the conclusion that something like Ladder is inevitable. This understanding further allows us to eliminate the redundant computation in the origin Ladder, and to only retain its essence. We also give an upper bound. But we do not stop there. We interpret this upper bound and use it as a tool to understand the advantages as well as limitation of Ladder when used in practice.

2 Leaderboard failure

In this sections, we show some examples where the leaderboard is hackable if it releases certain information. With these examples, we know at least what to avoid when building a leaderboard.

2.1 Full-information leaderboard is hackable

In this subsection, we show that if a leaderboard shows the score of each submission, this leaderboard is easy to hack.

Supposing that the validation set contains \( n \) different data points \( S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \), where \( y_i \in \{0, 1\} \) for each \( i \). The participant is expected to build a function \( f = f(x) \), so that \( f(x) \) is a good estimator of \( y \). Let the score be the accuracy of this estimator, which is defined as \( \text{score}(f) = \frac{1}{n} \sum_{i=1}^{n} 1_{\{y_i = f(x_i)\}} \) on the validation set. Every time the participant submits his \( \hat{y}_i = f(x_i) \) to the host, the host shows the score of \( f \) to the participant via the leaderboard. We show that this kind of leaderboard is easy to hack.

\( \tilde{O}() \) stands for omitting the logarithm term.
To hack this leaderboard, we perform a boosting attack. The idea is that if we have many independent submissions, whose accuracy are only a little higher than 0.5, then we can combine them via majority vote policy to construct a submission whose accuracy is much higher than 0.5.

In detail, we randomly pick a vector \( u \in \{0, 1\}^n \). If its accuracy is higher than 0.5, then we keep \( v = u \), and otherwise \( v = 1_n - u \). Having got \( m \) such vectors \( v^1, v^2, \ldots, v^m \), we construct the submission \( \hat{y}^m = (\hat{y}_1^m, \hat{y}_2^m, \ldots, \hat{y}_n^m)^T \), where \( \hat{y}_i^m \) equals to 1, if \( \frac{1}{m} \sum_{j=1}^{m} v_i^j > 0.5 \), and equals to 0 otherwise.

Figure 1 shows the result of this attack on a leaderboard of 1000 samples. We see that within \( 10^3 \) submissions, the hacker’s score climbs from 0.5 to 0.8 on the leaderboard. Therefore, in order to protect the leaderboard from the boosting attack, we cannot release information each time there is a submission. In consequence, we adopt the idea that the leaderboard gives the participant feedback only when his score is higher than the highest in the past.

### 2.2 High-precision leaderboard is hackable

Normally, a leaderboard shows two things – score and rank. In this subsection, we show that if a leaderboard precisely reflects the ranks, then this leaderboard is easy to hack.

For this, we consider a minimal leaderboard, which shows nothing other than the ranks. In other words, the participants are not able to observe the scores. Furthermore, inheriting the argument from the previous subsection, the leaderboard uses the highest score that a participant has ever achieved to compute the rank. In other words, a participant knows nothing even if he beats his old scores unless his new score is higher enough to beat another participant, whose rank was higher than his.

This leaderboard displays really little information. However, even with so little information displayed, it is still hackable. For this, we perform a brute-force enumeration attack. Precisely, the hacker signs up two accounts A and B. At first, he uses A to submit a random guess \( u^1 \), and he gets a rank \( a_1 \) for A. Then, he flips one component in this submission (say, \( u^1_1 \) from 0 to 1, or from 1 to 0), and uses B to submit it as \( u^2 \). He will get a rank \( b_1 \) for B, which is different than \( a_1 \). Let us assume that \( b_1 \) is higher than \( a_1 \)(otherwise, we just switch the name of account A and B). Then, he flips an unchanged

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2Actually this is not really a boosting technique, but we use the same terminology as in [1] here.
component (say $u^3_2$) and switches to A to submit it as $u^3$. The score $u^3$ yields is either higher or lower than $u^2$. If it is lower than $u^2$ (must be equal to $u^1$ in this case), then he sees no change on A’s rank. In this case, he repeats this step by flipping another component (say $u^3_2$) until it is higher than $u^2$ or all components have been flipped once. If it is higher than $u^2$, since the leaderboard precisely reflects the rank, it must move A’s rank from $a_1$ to $a_2$, which is higher than $b_1$. Once again, the hacker switches to the account B and repeats the process… He gets $a_1 < b_1 < a_2 < b_2 < a_3 <$ … Since the score is bounded by 1, and each score increment is constant, the hacker finally gets the score 1, which also means getting all answers right and ranking the highest on the leaderboard.

With this simple attack, we show that as long as the leaderboard precisely reflects the rank, a hacker equipped with two accounts can achieve arbitrarily high score. Therefore, a leaderboard should never reveal precise ranks. In other words, there are cases where two participants with different scores (this difference will not be observable) see them ranked together on the leaderboard.

### 3 Simplified Ladder leaderboard

In the previous section, we learned that a leaderboard should avoid some pitfalls. In this section, we show that the Ladder leaderboard [1] successfully avoids them. We first introduce Ladder and simplify it, and then demonstrate its robustness against boosting and enumeration attacks. Throughout this paper, we use the following notation.

**Notation.** $\lfloor x \rfloor_\eta$ denotes the number $x$ rounded to the nearest integer multiple of $\eta$; $\lceil x \rceil_\eta$ to the nearest not higher than $x$; $\lfloor x \rfloor_\eta$ to the nearest not lower than $x$. $\eta$ is a number in $\langle 0, 1 \rangle$, and is usually among the values 0.1, 0.01, etc.. When $\eta$ is missing, it is consider to be 1 in convention. $\log x$ denotes the binary logarithm.

The idea of Ladder is simple. The leaderboard only shows the best score that a participant has ever achieved, and updates it only when a record-breaking score is higher than it by some margin $\eta$ (Algorithm 1). Notice that there is a parameter $\eta$ in this algorithm. To overcome this inconvenience, [1] also suggests a parameter-free Ladder leaderboard. However, this parameter-free version is hackable (Figure 1). The method is to make a first submission containing half 1 and half 0. Then switch the place of a 1 and a 0 in each submission.

In this paper, we give a simplified Ladder version (Algorithm 2) as well as a way to choose the optimal value of $\eta$. Comparing these two algorithms, the only tiny difference is the condition in Step 3 – we drop the margin $\eta$. This raises naturally the question whether this modification breaks the algorithm? No. In fact, the margin $\eta$ is already captured in the assignment $R_t \leftarrow \lceil h_t \rceil_{\eta}$ by the precision $\eta$. Since $R_{t-1}$ is always an integer multiple of $\eta$, $R_t$ can be greater than $R_{t-1}$ if and only if $h_t$ is higher than $R_{t-1}$ by a margin of $\frac{\eta}{2}$. The simplification does not stop here. Indeed, Step 3 can be rephrased as $R_t = \max \left( R_{t-1}, \lceil h_t \rceil_{\eta} \right)$. So the idea of the simplified Ladder leaderboard is just to authentically display the best score achieved by each participant so far, but with a certain level of precision $\eta$.

**Algorithm 1** Original Ladder [1]

Assign initial score $R_0 \leftarrow -\infty$.

for round $t = 1, 2, \ldots$ do

1. Receive submission $u^t$
2. $h_t \leftarrow$ score of $u^t$
3. If $h_t > R_{t-1} + \eta$ then $R_t \leftarrow \lceil h_t \rceil_{\eta}$ else $R_t \leftarrow R_{t-1}$
4. Show $R_t$ on the leaderboard

end for

Note: $\lceil x \rceil_{\eta}$ denotes the number $x$ rounded to the nearest integer multiple of $\eta$. 

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Algorithm 2 Simplified Ladder

Assign initial score $R_0 \leftarrow -\infty$. 

for round $t = 1, 2, \ldots$ do 
1. Receive submission $u^t$
2. $h_t \leftarrow$ score of $u^t$
3. If $h_t > R_{t-1}$ then $R_t \leftarrow [h_t]_\eta$ else $R_t \leftarrow R_{t-1}$
4. Show $R_t$ on the leaderboard 
end for

Note: $[x]_\eta$ denotes the number $x$ rounded to the nearest integer multiple of $\eta$.

This understanding is very helpful. On the one hand, it simplifies the implementation of the Ladder leaderboard. The practitioners have less chance to make an error (e.g., by accidentally dropping the precision $\eta$ or configure a smaller one). On the other hand, it greatly simplifies the analysis. $\eta$ here is no longer an algorithmic parameter. It is instead the precision which the leaderboard offers.

After the presentation of Ladder algorithm, now let us try to answer this question: does Ladder avoid the pitfalls mentioned above? Yes. On the one hand, it only reveals the highest score so far. On the other hand, it does not give arbitrarily precise information – a participant yielding 0.644 is not distinguishable from another participant yielding 0.636 when $\eta = 0.01$.

But there still remain questions that whether Ladder is hackable. Is it robust against all attacks besides the above mentioned ones? The answer is yes, provided that the attacker does not possess many accounts. And the robustness is proportional to the cubic root of the size of the validation set. If we want the precision $\eta$ to be 0.1, we should have $10^3$ samples; if $\eta = 0.01$, we will need $10^6$ samples. This will be proved in the next section.

Here again our understanding of Ladder contributes. If $\eta$ is too large, which means that the precision is low, the participants will not be distinguishable – they are clustered on the leaderboard. Such a leaderboard is not informative. If $\eta$ is too small, which means the precision is too high and the leaderboard reveals too much information, there will not be enough samples to maintain the authenticity of the leaderboard – the leaderboard is easy to hack or overfit. Such a leaderboard is false. This trade-off is the central topic of the next section.

In the rest of this section, we present some results about some attacks on Ladder. Figure 1 shows that Ladder is robust against the boosting attack. Figure 2 shows some brute-force enumeration attacks on Ladder. In these examples, to defend against the attacks, Ladder uses less samples than necessary, for the brute-force is not very efficient, since it does not make use of all information available on the leaderboard.

Figure 2: Attack on Ladder. Each trajectory is correspondent to an attack. Left: $n=1000$, $\eta=0.01$. Right: $n=20000$, $\eta=0.001$. 

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4 Sample complexity

In this section, we present the sample complexity of the Ladder leaderboard. We show that \( \eta \) is not only the display precision of the leaderboard, but also the optimal value of \( \eta \) is the lowest leaderboard error possible. This optimal value is \( \eta^* = \tilde{O}\left(\sqrt[3]{\frac{M}{n}}\right) \), where \( M \) is the number of accounts and \( n \) is the number of samples in the validation set.

Suppose that our data \((X,Y)\) lie in some space \( \Omega \times \{0,1\} \). They follow a distribution \( D \) on this space. Validation set \( S = \{(x_1,y_1), \ldots, (x_n,y_n)\} \) are samples drawn i.i.d. from this distribution. A classifier of this problem is represented by the function \( f : \Omega \to \{0,1\} \). The accuracy of this classifier is defined as

\[
R_D(f) := \Pr(f(X) = Y).
\]

Its accuracy on the validation set is defined as

\[
R_S(f) := \frac{1}{n} \sum_{i=1}^{n} I(f(x_i) = y_i),
\]

where \( I(\cdot) \) is the indicator function.

\( R_S(f) \) can be seen as an estimator of \( R_D(f) \), whose error could be measured by the quantity \( |R_S(f) - R_D(f)| \). Normally, this error should be small \([4, 5, 6, 7]\). However, due to the overfitting or hack by repeated and adaptive submissions, this error could grow larger and larger. As this error grows, the leaderboard is no longer a qualified index of the performance of participants. The scores it displays no longer reflect the true accuracy of the models, and the ranks it shows do not truly imply that one participant’s model is better than another’s. This is why the traditional leaderboard fails.

Since \( R_S(f) \) is no longer a good estimator of \( R_D(f) \), one may ask whether there exist other estimators. \([2, 3]\) show that no computationally efficient estimator can achieve error \( o(1) \) on more than \( n^{2+o(1)} \) adaptively chosen functions in a traditional leaderboard. Therefore, \([1]\) as well as this article tries another approach: the Ladder leaderboard.

In Ladder, the leaderboard only displays the best ever score that an account has achieved \( R_t := \max_{1 \leq i \leq t} R_S(f_i) \), where \( f_i \) is the function which characterizes the \( i \)-th submission associated with a given account. Thus, at the moment \( t \), the error of the score displayed on the leaderboard could be measured by the quantity \( |R_t - \max_{1 \leq i \leq t} R_D(f_i)| \). Across the time, the leaderboard error of \( R_1, \ldots, R_k \) of a single account is measured with

\[
\text{lberr}(R_1, \ldots, R_k) := \max_{1 \leq t \leq k} \left| R_t - \max_{1 \leq i \leq t} R_D(f_i) \right|.
\]

A small leaderboard error means that the score displayed on the leaderboard is close to the best score the account in question gets on the underlying true distribution.

\([1]\) gives an upper bound to the leaderboard error. However, it does not take into consideration the fact that a participant may possess multiple accounts, in which case their reasoning breaks. In this paper, we take that into consideration and our upper bound is slightly tighter than theirs (logarithmic factor) when degenerated to one-person-one-account case.

If a participant has multiple accounts, he can then switch among different accounts to submit successive submissions. His submission thus does not depend only on the history of the current account, but also on the histories of other accounts. Denote

\[
\tilde{\mathcal{F}}_t = \left\{ f^m_i : 1 \leq i \leq k_m, 1 \leq m \leq M, \sum_{m=1}^{M} k_m = t \right\}
\]
as the submission history right after the moment \( t \), where \( f_i^m \) signifies using account \( m \) to submit account \( m \)'s \( i \)-th submission, and \( k_m \) is the subtotal submissions associated with account \( m \). Denote \( \mathcal{R}_t = \left\{ R_i^m : 1 \leq i \leq k_m, 1 \leq m \leq M, \sum_{m=1}^{M} k_m = t \right\} \) as the feedback (score) history associated with \( \mathcal{F}_t \).

**Theorem.** Given a competition with a validation set of \( n \) samples, where the Ladder leaderboard employs a display precision of \( \eta \), and each participant can possess at most \( M \) accounts. For any set of \( k \) (adaptively chosen) classifiers \( \mathcal{F}_k \) submitted by a participant, his scores \( \mathcal{R}_k \) displayed on the leaderboard satisfy

\[
\Pr \left\{ \max_{1 \leq t \leq k_m, 1 \leq m \leq M} \left| R_i^m - \max_{1 \leq i \leq t} R_D(f_i^m) \right| > \eta \right\} \leq \exp \left( -\frac{\eta^2 n}{2} + \left( \frac{M}{\eta} + 1 \right) \log 2k + 1 \right).
\]

In particular, for some \( \eta = O \left( \sqrt{\frac{M \log k}{n}} \right) \), Ladder achieves with high probability: for any \( m = 1, \ldots, M \),

\[
\text{lberr}(R_1^m, \ldots, R_{k_m}^m) \leq O \left( \sqrt{\frac{M \log k}{n}} \right).
\]

Here, we successfully thrust the number of submissions \( k \) into the logarithmic factor. Thus, the leaderboard error is no longer sensitive to the number of submissions. A participant can submit as many times as he wishes (if he is able of course). However, we notice that the number of accounts \( M \) is still outside of the logarithmic factor, which means that the leaderboard error grows quickly when \( M \) grows. Although it is only an upper bound, which is less persuasive than a lower bound, we can provide a counter example to illustrate the effect of multi-account. Consider the extreme case where the participant submits each submission with a brand new account every time (i.e., \( M = k \)), the leaderboard error grows quickly with the submissions. Indeed, Ladder shows no difference from the traditional leaderboard in this case.

The theorem’s aim is to prove a small leaderboard error. But why does it matter? What is the relation to the robustness of a leaderboard? The consequence of a small leaderboard error means that a participant’s score sticks to his score on the ground truth. It is not likely that he could climb up on the leaderboard either by overfitting or by hack. If he marks a leap on the leaderboard, chances are that he really improved his prediction model.

Therefore, the theorem can be interpreted as: when the display precision of ladder is set to the optimal value \( \eta^* = O \left( \sqrt{\frac{M \log k}{n}} \right) \), a participant who gets a score \( s \) (an integer multiple of \( \eta^* \)) has large chance that his true score on the ground truth is within \([s - \eta^*, s + \eta^*]\). If two participants A and B get the score \( s_A \) and \( s_B \) respectively, where \( s_A - s_B > 2\eta^* \), chances are that A really outperforms B. Particularly, a hacker has little chance to get a score higher than \( \frac{1}{2} \eta^* \), since he learns nothing and his true score should be the same as the random guess.

Naturally, we would like \( \eta^* \) small. This depends on \( n \). We see that to achieve a small \( \eta^* = \epsilon \), we will need \( O \left( \frac{M \log k}{\epsilon^2} \right) \) samples.

## 5 Proof of Theorem

From the state-of-art literature [4, 5, 6, 7], we already have

\[
\Pr \left\{ \max_{1 \leq i \leq k} |R_S(h_i) - R_D(h_i)| > \epsilon \right\} \leq 2k \exp(-2\epsilon^2 n),
\]

(2)
for a series of functions \( h_1, \ldots, h_k \) which are independent of the validation set \( S \). This inequality is quite close to our destination. However, because of the sequential and adaptive nature of our problem, \( h_{t+1} \) is a function of \( R_S(h_1), \ldots, R_S(h_t) \), which means that it is not independent of \( S \). Thus, we cannot apply the above inequality directly. The technique employed in this proof is to eliminate the dependence by enumerating all possible realizations.

\[ \Pr \left\{ \max_{g} |R_S(g) - R_D(g)| > \frac{\eta}{2} \right\} \leq 2 \times 2^\left(\frac{M+1}{\eta}\right) \log 2k \exp \left(-\frac{\eta^2 n}{2}\right). \]

Then, we can apply \( \eta = \eta/2 \):

\[ \Pr \left\{ \max_{g} |R_S(g) - R_D(g)| > \frac{\eta}{2} \right\} \leq 2 \times 2^\left(\frac{M+1}{\eta}\right) \log 2k \exp \left(-\frac{\eta^2 n}{2}\right). \]

The left side equals exactly

\[ \Pr \left\{ \max_{h \in G_k} |R_S(h) - R_D(h)| > \frac{\eta}{2} \right\}, \]

while the right side is bounded by

\[ \exp \left(-\frac{\eta^2 n}{2} + \left(\frac{M}{\eta} + 1\right) \log 2k + 1\right), \]

which is exactly the right side of \( \square \).

Conditioned on the event \( \{\max_{h \in G_k} |R_S(h) - R_D(h)| \leq \frac{\eta}{2}\} \), we have

\[ \max_{1 \leq t \leq k, 1 \leq m \leq M} \left| \max_{1 \leq i \leq t} R_S(f_i^m) - \max_{1 \leq i \leq t} R_D(f_i^m) \right| \leq \frac{\eta}{2}. \]

And since we have

\[ \left| R_t^m - \max_{1 \leq i \leq t} R_S(f_i^m) \right| \leq \frac{\eta}{2} \]
because of the rounding error, by the triangular inequality, we get
\[
\max_{1 \leq t \leq k, 1 \leq m \leq M} \left| R_t^m - \max_{1 \leq i \leq t} R_D(f_t^m) \right| \leq \eta,
\]
which is exactly what we want on the left side of (1). \qed

6 Discussion
Ladder is vulnerable if the number of accounts each participant can hold is unlimited. It is possible to launch a boosting attack on Ladder leaderboard by using a brand-new account for each submission (Figure 1). Given limited number of accounts (e.g. one account for each participant), Ladder is robust against the number of submissions. However, compared with the quadratic sample complexity of general statistical / machine learning tasks, the cubic sample complexity of the Ladder leaderboard may still remain a bit too expensive. For a mere 0.01 leaderboard error, the validation set has to have $10^6$ samples. This is not possible in most competitions. Even if it is, we may still have questions such as why not put these samples into the training dataset so as to enable the participants to use more complex models. This makes the loss of Ladder more than its gain. On the other hand, we do not know whether this cubic root upper bound is tight. We have yet found an efficient attack algorithm that could achieve this upper bound, nor have we discovered a tight lower bound. That is to say, Ladder may actually work better than we expected here. In practice, the competition hosts employ as well other measures, such as limiting the number of submissions per day, disqualifying participants secretly signing up other accounts etc., to strengthen the accuracy of the leaderboard. These measures could be combined with Ladder so as to provide a more accurate leaderboard than the traditional one.

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