How XCS Can Prevent Misdistinguishing Rule Accuracy: A Preliminary Study

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ABSTRACT

On the XCS classifier system, an ideal assumption in the latest XCS learning theory means that it is impossible for XCS to distinguish accurate rules from any other rules with 100% success rate in practical use. This paper presents a preliminary work to remove this assumption. Furthermore, it reveals a dilemma in setting a crucial XCS parameter. That is, to guarantee 100% success rate, the learning rate should be greater than 0.5. However, a rule fitness updated with such a high learning rate would not converge to its true value so rule discovery would not act properly.

CCS Concepts

•**Computing methodologies** → **Rule learning;** *Classification and regression trees;*

Keywords

learning classifier system, rule-generation, theory

1. INTRODUCTION

On evolutionary rule-based learning [?, ?], there lacks of modern theoretical progress [?]. For the most popular version i.e. XCS-based systems (e.g. [?, ?, ?, ?, ?]), the latest XCS learning theory [?] in 2017 makes progress but is still limited. While this theory is designed for classification, it derives an optimum XCS parameter setting for the learning rate β that guarantees XCS distinguishes an accurate rule from any other inaccurate rules under certain assumptions. Besides, it reveals that β can be set to a smaller value than its standard value 0.2 [?] for high dimensional problems [?].

However, the XCS learning theory cannot guarantee that XCS distinguishes accurate rules from the inaccurate ones with a 100% success rate, due to an ideal assumption. For classification, a classification accuracy P_C of a rule can be a criteria for rule quality. The XCS learning scheme estimates an prediction error ϵ_n while sampling rewards, as an alternative to P_C. Then, XCS identifies a rule as accurate if its ϵ_n is smaller than a threshold ϵ_0, otherwise inaccurate. So, we should satisfy that the upper and lower bounds of ϵ_n of truly accurate and inaccurate rules are respectively smaller and larger than ϵ_0. However, this theory assumes *approximated* lower/upper bounds given by the true value of P_C to sidestep the uncertainty of reward sampling. Hence, due to an approximation gap against reality, an inaccurate rule may have ϵ_n smaller than its approximation and so ϵ_0.

This paper presents a preliminary work of a revised XCS learning theory that guarantees XCS perfectly distinguishes the accurate rules from the inaccurate rules. We here do not use any ideal assumption using the true value of P_C in calculating the lower/upper bounds of the prediction error. Instead, we derive equations of the *actual* lower/upper bounds while handling the uncertainty of reward sampling. Besides, we reveal that, there is a dilemma of when boosting both the learning capacity and the search capacity together.

GECCO '19 Companion, July 13–17, 2019, Prague, Czech Republic
© 2019 ACM. ISBN 978-1-4503-6748-6/19/07...$15.00
DOI: https://doi.org/10.1145/3319619.3321942

2. REVISED THEORY

Due to the limit of space, we here only show a preliminary result of theoretical conclusion. Besides, in this paper, we use the same matematical terminology as in [?, ?].

Maximum prediction error of accurate rules.

Since the completely accurate rule $cl(P_C{}^*)$ should receive only a constant value of received reward during the $n_{\min}$ update times, each r_k of the actual prediction given the estiamted equation for $\epsilon_{n_{\min}}(P_{C}{}^*_{\min})$ in [?] does not depend on the reward history. As a result, $\max\epsilon_{n_{\min}}(P_C{}^*)$ is equivalent to $\max\hat{\epsilon}_{n_{\min}}(P_C{}^*)$ which have been derived in [?];

$$\max\epsilon_{n_{\min}}(P_C{}^*) = r_{\max}(1-\beta)^{n_{\min}} + r_{\max}n_{\min}\beta(1-\beta)^{n_{\min}-1}. \quad (1)$$

Hence, this is the actual upper bound of prediction error for the accurate rules.

Minimum prediction error of inaccurate rules.

As a preliminary work, we here only consider an inaccurate rule $cl(P_C{}')$ having a true classification accuracy $0.5 \leq P_C{}' < P_C{}'_{max}$. Since we can consider possible combinations of $r_{\min}$ and $r_{\max}$ during $n_{\min}$ update times, a problem is now to specify the reward history that minimizes the actual prediction error. Then, such a reward history is given such that the actual prediction can be maximized for $P_C{}' \geq 0.5$.

Let $\mathbf{R}'_{\max} = [r_1, \cdots, r_{n_{\min}}]$ be the latest $n_{\min}$ reward history that maximizes the prediction. We can identify $\mathbf{R}'_{\max} = [r_{\min}, r_{\max}, \cdots, r_{\max}]$ where the oldest reward r_1 is $r_{\min}$ and other rewards are $r_{\max}$. Consequently, $P_C{}'$ calculated from $\mathbf{R}'_{\max}$ is corresponding to the upper bound of $P_C{}'$ i.e. $P_C{}'_{\max}$.

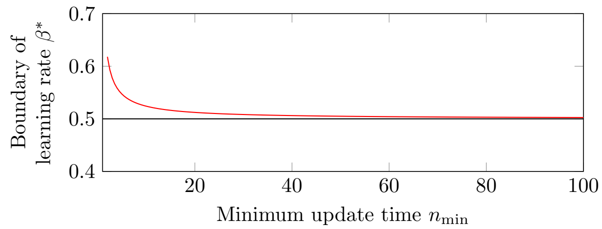

Figure 1: The boundary value of learning rate β^* given by (??); β^* (red line) converges near to 0.5.

Then, $\epsilon_{n_{\min}}(P_C{}'_{\max})$ calculated from $\mathbf{R}'_{\max}$ can be;

$$\begin{aligned}\epsilon_{n_{\min}}(P_C{}'_{\max}) &= (1-\beta)^{n_{\min}}\epsilon_I + \beta(1-\beta)^{n_{\min}-1}|r_{\min} - p_I| \\ &\quad + \sum_{k=2}^{n_{\min}} \beta(1-\beta)^{n_{\min}-k}|r_{\max} - p_{k-1}(P_C{}'_{\max})| \\ &= (1-\beta)^{n_{\min}}\epsilon_I - (n_{\min}-2)\beta(1-\beta)^{n_{\min}-1}p_I \\ &\quad + (n_{\min}-1)\beta(1-\beta)^{n_{\min}-2}r_{\max}. \qquad (2)\end{aligned}$$

Let us further minimize $\epsilon_{n_{\min}}(P_C{}'_{\max})$ in terms of the variables p_I and ϵ_I. Since $\epsilon_{n_{\min}}(P_C{}'_{\max})$, (**??**) can be monotonically decreasing and increasing for p_I and ϵ_I respectively, and so we can determine $p_I = r_{\max}$ and $\epsilon_I = 0$. Hence, the minimum value can be;

$$\min \epsilon_{n_{\min}}(P_C{}') = \beta(1-\beta)^{n_{\min}-2}\left[1 + (n_{\min}-2)\beta\right] r_{\max}. \qquad (3)$$

Hence, for $0.5 \le P_C{}' < P_C{}'_{max}$, all possible values of $\epsilon_n(P_C{}')$ are always larger or equal to the actual lower bound given by (**??**).

Theoretical parameter settings.

Finally, we determine the theoretical parameter setting of ϵ_0 and β from a boundary condition. The original learning theory employs the boundary condition $\max \hat{\epsilon}_{n_{\min}-1}(P_C{}^*) = \min \hat{\epsilon}_{n_{\min}-1}(P_C{}')$ i.e. at one update time before $n_{\min}$ according to a fact that $\min \hat{\epsilon}_n(P_C{}')$ i.e. the approximated lower bound can be monotonically increasing for n. However, in practice, we can now see $\min \epsilon_{n_{\min}}(P_C{}')$, i.e. the actual lower bound is monotonically decreasing for $n_{\min}$ and so we should not use the original boundary condition. Accordingly, we directly solve the following inequality for β; $\max \epsilon_{n_{\min}}(P_C{}^*) < \min \epsilon_{n_{\min}}(P_C{}')$. Then, this expression can be a quadratic inequality for β and so β must be larger than a boundary value β^* given by;

$$\beta^* = \frac{3 - n_{\min} - \sqrt{n_{\min}^2 + 2n_{\min} - 3}}{6 - 4n_{\min}}. \qquad (4)$$

Hence, when we set $\beta > \beta^*$ and $\epsilon_0 = \min \epsilon_{n_{\min}}(P_C{}')$ calculated from β, $\max \epsilon_{n_{\min}}(P_C{}^*)$ is always smaller than ϵ_0. Therefore, our goal can be satisfied for any rules which have been updated more than or equal to $n_{\min}$ update times. In other words, under the definition that P_C is calculated from the latest $n_{\min}$ rewards, XCS with our theoretical parameter settings does not misdistinguish inaccurate rules as accurate.

3. DILEMMA

As explained in [**?**], the value of β determines whether the prediction error converges to its true value. The existing learning theory recommends β is set to as small value as possible. However, our theoretical result reveals that β should be set to an exceptionally high value. Specifically, as shown in Fig.**??**, β^* is always larger than 0.5 for any values of $n_{\min}$; and β should be larger than β^*. Consequently, we cannot expect that the rule-fitness stably converges to its true value as well as the prediction error. Hence, the rule-fitness may not reliably identify the rules having a high classification accuracy. Consequently, GA would suffer to act with a proper evolutionary search. Thus, XCS would lose its search ability to find $cl(P_C{}^*)$ when having a learning capacity to perfectly distinguish $cl(P_C{}^*)$ from $cl(P_C{}')$.

4. CONCLUSION

This paper presented a preliminary work of to achieive that guarantees XCS distinguishes the accurate rules from the inaccurate rules with 100% success rate. Moreover, our theoretical result reveals a dilemma; XCS would lose search capacity to find $cl(P_C{}^*)$ when having a learning capacity to perfectly distinguish the $cl(P_C{}^*)$ from the $cl(P_C{}')$. In furture work, we should exntend our result to cover *all* poissible inaccurate rules, i.e., $P_C{}' \le 0.5$ as well as $P_C{}' \ge 0.5$.

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