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Uncertainty-Aware Reinforcement Learning for Risk-Sensitive Player Evaluation in Sports Game (/pdf?id=QoHSzxp7tSN)

Anonymous

17 May 2022 (modified: 20 May 2022) NeurIPS 2022 Conference Blind Submission Readers: Conference, Paper4391 Senior Area Chairs, Paper4391 Area Chairs, Paper4391 Reviewers, Paper4391 Authors Show Revisions (/revisions?id=QoHSzxp7tSN)

Rebuttal Revision

Keywords: Reinforcement Learning, Uncertainty Estimation, Sports Analytic, Agent Evaluation

TL;DR: We design a data-driven RL framework that enables post-hoc calibrations on action values according to their aleatoric and epistemic uncertainties.

Abstract: A major task of sports analytics is player evaluation. Previous methods commonly measured the impact of players' actions on desirable outcomes (e.g., goals or winning) without considering the risk induced by stochastic game dynamics. In this paper, we design an uncertainty-aware Reinforcement Learning (RL) framework to learn a risk-sensitive player evaluation metric from stochastic game dynamics. To embed the risk of a player's movements into the distribution of action-values, we model their 1) aleatoric uncertainty, which represents the intrinsic stochasticity in a sports game, and 2) epistemic uncertainty, which is due to a model's insufficient knowledge regarding Out-of-Distribution (OoD) samples. We demonstrate how a distributional Bellman operator and a feature-space density model can capture these uncertainties. Based on such uncertainty estimation, we propose a Risk-sensitive Game Impact Metric (RiGIM) that measures players' performance over a season by conditioning on a specific confidence level. Empirical evaluation, based on over 9M play-by-play ice hockey and soccer events, shows that RiGIM correlates highly with standard success measures and has a consistent risk sensitivity.

Supplementary Material: zip (/attachment?id=QoHSzxp7tSN&name=supplementary_material)

Revealed to Guiliang Liu, Yudong Luo, Oliver Schulte, Pascal Poupart

15 May 2022 (modified: 20 May 2022) NeurIPS 2022 Conference Submission

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[–] Official Review of Paper4391 by Reviewer kCNJ

NeurIPS 2022 Conference Paper4391 Reviewer kCNJ

12 Jul 2022 NeurIPS 2022 Conference Paper4391 Official Review Readers: Program Chairs, Paper4391 Senior Area Chairs, Paper4391 Area Chairs, Paper4391 Reviewers Submitted, Paper4391 Ethics Reviewers, Paper4391 Authors

Summary:

The authors develop an offline RL model for risk-sensitive agent evaluation and apply it to study player impact in sports games. Unlike previous approaches, their method RiGIM is sensitive to stochasticity in the environment (some situations have lower/higher variation in their outcomes) and can handle the OoD actions that plague Offline RL. Because they are focused on evaluation (and not control), the typical techniques for dealing with OoD actions (lowering action values or constraining the policy) will not work and so the authors develop a scalable density estimator based on normalizing flows. These techniques are evaluated on a large dataset of hockey and soccer games and correlated with traditional measures of impact.

Strengths And Weaknesses:
The paper is clearly written with consistent notation and the problem is well articulated. Both the problem statement and the techniques used to solve it are novel to my knowledge. Furthermore the approach is demonstrated on a large dataset of practical importance with potentially promising results. The main weaknesses are related to the clarity and interpretation of the evaluation (expanded on in the Question section). The evaluation of the results are confusing and it is not clear how this technique should be measured or used.

Small issues:

Line 37-39 citation of what algorithms are being contrasted here. What is the x-axis supposed to represent in (a)-(d) in Figure 1?

Grammar: "We measure whether RiGIM is sensitive to the risk by its correlation" (Line 287).

Lines 294-296 are repetitive with 282-283

Questions:
Can you give some intuitions for the case study results in Table 1/2. The only comment is that there are more defensemen in the higher confidence top 10 -- although this is true empirically -- why is this a prediction of higher confidence? It doesn't seem to clearly correlate with the other metrics shown. Tyler Seguin and Connor McDavid have similar stats and play in the same position so what accounts for them being in the different top 10 lists? The authors mention a couple of qualitative findings e.g., "low confidence favors centers, strong scoring ability) but its not clear what is driving these predictions. How would a layperson use this tool?

For tables 4/5/6, why was c set to 0.5 instead of fit on the validation set? How would one decide on a value for c in practice?

In table 6, many of the bolded numbers are not different at a level of statistical significance. Ideally, the algorithm can be run more times for the camera ready to reduce the uncertainty about performance.

Why is the correlation with traditional metrics a good way of measuring success? The "success measures" are very simplistic features of the game so it could be that a better correlation with these measures is actually a signal that the algorithm is doing something naive rather than sophisticated.

Why do traditional metrics better correlate with risk-seeking versions of (smaller values of c)?

Will the post-hoc calibration techniques developed in this work also apply to the offline RL control setting? Might this be a better approach than constraining the actions that the agent can take?

Limitations:
Limitations are addressed.

Ethics Flag: No

Soundness: 3 good

Presentation: 4 excellent

Contribution: 3 good

Rating: 6: Weak Accept: Technically solid, moderate-to-high impact paper, with no major concerns with respect to evaluation, resources, reproducibility, ethical considerations.

Confidence: 3: You are fairly confident in your assessment. It is possible that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work. Math/other details were not carefully checked.

Code Of Conduct: Yes

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Official Review of Paper4391 by Reviewer tcWQ

NeurIPS 2022 Conference Paper4391 Reviewer tcWQ

02 Jul 2022 NeurIPS 2022 Conference Paper4391 Official Review Readers: Program Chairs, Paper4391 Senior Area Chairs, Paper4391 Area Chairs, Paper4391 Reviewers Submitted, Paper4391 Ethics Reviewers, Paper4391 Authors

Summary:
This papers uses reinforcement learning for player evaluation in a sports game, ice hockey. The Risk sensitive Game Impact Metric is proposed. This paper is about applying a range of analysis techniques in a soccer-related setting. It is admirable that the authors set out to provide a practical use of data in football ("This study aims to help soccer managers make decisions based on data when they formulate their team tactics."). However, I'm afraid that this is too ambitious.

Strengths And Weaknesses:
No realistic contribution to the real world The challenge that the authors took upon themselves, determining which formation to use against a specific opponent, is a more complex problem than the authors make it appear to be. It's not just a matter of selecting 4-4-2 or 4-3-3 prior to each match, it's a result of the specific strengths of the players in a team, the form of these players and the tactical plan of a team that they are working on a whole season long. In other words, even if an analysis could provide the best formation to be adopted, it would be very difficult to actually use that advice if it would be different from what the coaches were going for anyway. So, for sure, the authors should paint a more realistic picture of what the use of their work might be.

Poor overview of existing literature Unfortunately, there are some issues with the storyline the authors present. First of all, the authors sketch an incorrect picture of the existing literature of science in football:

• "However, very few use data science and artificial intelligence for soccer tactics." This is inaccurate, especially in recent years the use of DS and AI in soccer has exploded. See for an extensive review of soccer-related scientific literature Goes et al. (2021): Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. This paper includes a large amount of relevant literature that was published until 2020. In the meantime, many more papers have come out that could be relevant for your work. • Reference number [4] is supposed to be about transfer fees and the use of data, instead it is about big data and the modern industry (with one anecdotal mention of football, but not transfer fees). • Reference number [5], used to support the claim that Germany's performance was influenced by data analysis, is about 'the internet of things'. I do not see a relationship between the text and the reference. • Reference number [6] holds no relation to the statement in the text. That paper was about the influence of leadership types, and not about how difficult it is to analyze tactics in soccer.

The authors need to properly build their story with appropriate (up-to-date) scientific literature.

Lack of critical thinking The authors fail to critically assess the work of others that they discuss, but also of themselves. I need to know whether a technique/finding is appropriate for the current setting, and why. An example of lack of critical thinking: Section 5.4 contains a summation of comparisons that were made, but no reflections whatsoever. First of all, I'd expect a brief statement of what the comparison yielded. And, second of all, I'd expect a critical evaluation of the strengths and weaknesses of such a comparison.

Poor writing The English language (grammar and spelling) is fine, but the writing is too vague and unclear. For half of what's written I was left wondering what the authors were referring to precisely. An example of poor writing: The last paragraph of section 6 becomes a bit difficult to read. These sentences appear to be English, but I have no clue what you are trying to say: "The results of this study make it possible to conceive of soccer tactics based on data obtained when managers devise tactics for real soccer matches."

Altogether I would recommend to reject the current submission.

Questions:
Unclear why And finally, at the end of the paper I'm wondering 'but why?' and also 'to what other situations is this relevant?'

Limitations:
Yes, no ethical problems with this work.

Ethics Flag: No
Soundness: 1 poor
Presentation: 2 fair

Contribution: 1 poor

Rating: 2: Strong Reject: For instance, a paper with major technical flaws, and/or poor evaluation, limited impact, poor reproducibility and mostly unaddressed ethical considerations.

Confidence: 5: You are absolutely certain about your assessment. You are very familiar with the related work and checked the math/other details carefully.

Code Of Conduct: Yes

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[−] **Official Review of Paper4391 by Reviewer mdqR**

NeurIPS 2022 Conference Paper4391 Reviewer mdqR

26 Jun 2022 NeurIPS 2022 Conference Paper4391 Official Review Readers: Program Chairs, Paper4391 Senior Area Chairs, Paper4391 Area Chairs, Paper4391 Reviewers Submitted, Paper4391 Ethics Reviewers, Paper4391 Authors

Summary:

The paper addresses the problem of evaluating player behavior in games based on the expected value and uncertainty of actions taken, specifically when examining data obtained from live sports (ice hockey and soccer).

The authors propose a model to decompose games into a series of episodes with inherent stochasticity ("aleatory uncertainty") and limited observational data ("epistemic uncertainty"). The model uses distributional reinforcement learning to address stochastic dynamics. The model also filters samples using a density estimator to address out-of-distribution data and offline data sampling sparsity. Evaluation results show better correlations to game metrics (like scoring goals) when compared to alternative accepted methods and small errors when predicting scoring probabilities in different conditions.

Strengths And Weaknesses:

strengths

The method improves over other methods. The results for predict scoring chances are particularly encouraging. The correlational results are more mixed, though the family of proposed methods (*-RiGIM) as a whole obtain competitive results. The bootstrap repetitions in the appendix are convincing that the results are not mere sampling artifacts (though would be welcome in the main text).

The paper's originality lies in quantifying risk taking (seeking) behavior from offline and potentially sparse data. The core techniques are not particularly novel (distributional RL & density estimation), but they are clearly explained and integrated into a relevant application context. Many analytics practitioners would benefit from understanding these methods and considering the use of uncertainty estimates in their algorithms.

The exposition is clear and generally easy to follow. Some of the proofs require further background knowledge (not surprising) and the dataset was not clearly explained in the main text. These are minor flaws and less important than conveying the core approach and goals.

The method shows promising generality. Evaluations on both ice hockey and soccer are favorable, suggesting the decomposition can impact a variety of sports analytic fields (among other domains). This is a welcome advance given the increasing adoption of analytics in many sports and the diversity of existing practices for making human judgments of player performance. Generalization to other offline RL tasks remains an open question, but suggests a broader potential audience at NeurIPS.

The evaluations demonstrate rigor in handling real-world offline data. For example, splitting time periods and ensuring test data comes later, as would occur when deploying this approach in real world applications.

weaknesses

The RiGIM model results (Figure 5) are ambiguous. The error bars for ablations heavily overlap the full model, suggesting that the simpler Na-RiGIM may be sufficient in most contexts. The text would benefit from addressing the differences in performance and why they may (not) obtain in this case.

Limited technical novelty. Distributional Bellman and the feature density estimator are both adapted from prior work. The novelty lies more in application than new major results. This is a minor weakness: combining the methods is not trivial.

It is not clear why risk-sensitive evaluation is valuable to practitioners. Given the post-hoc nature of the analysis, risk quantification will not help balancing exploration and exploitation. This opens the question as to how significant the results are to practitioners. The text would benefit from explicitly addressing this point (see question below).

Questions:
[Q0] What does employing a risk-based cutoff add to the existing analyst techniques? Having a variety of cut-off thresholds (like all hyperparameters) makes assessment more complex, begging the question: what are the benefits for these additional complexity costs? The empirical results make one useful case about better calibration, but the text would benefit from clarifying the impact and significance to how analysts (or players or coaches) would use this new information.

[Q1] What new insights can be obtained from the rankings provided? How are these of interest to those with domain expertise? Practitioners?

[Q2] How does RiGIM scale? How much does the model improve as the number of matches observed increases? How effective is the model for evaluating new players (presumably since the player is not a feature of the model cold start problems should be lesser)? How does model training scale in terms of compute resources needed?

[Q3] (Table 4) Why might SI do so well at predicting Goals and Game Winning Goals compared to the alternatives? There is a substantial gap between the performance of SI and the runner up for Goals (0.596 vs 0.477) and GWG (0.409 vs 0.266). What is RiGIM failing to capture that SI does?

Limitations:
In terms of limitations, it would help to read some of the authors thoughts on scalability of this technique (mentioned above in the questions). What aspects of risk remain poorly disentangled that are worth further investigation?

The discussion of the negative impacts of increased player scrutiny is welcome in an era where greater analytics empowers audiences to (often harshly) critique players. I would suggest discussing some of the effects of sports analytics on the behavior of coaches (team decision-makers more broadly) when it comes to evaluating and understanding their players. New analytics can provide insight, but there is always the risk of Campbell's Law and increasing pressure on players to conform to metrics over good behavior (not new in the sense that scoring behavior is already tracked, but now with new measures).

Ethics Flag: Yes
Ethics Review Area: Privacy and Security (e.g., consent)
Soundness: 3 good
Presentation: 3 good
Contribution: 2 fair
Rating: 6: Weak Accept: Technically solid, moderate-to-high impact paper, with no major concerns with respect to evaluation, resources, reproducibility, ethical considerations.
Confidence: 3: You are fairly confident in your assessment. It is possible that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work. Math/other details were not carefully checked.
Code Of Conduct: Yes

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