Domain-Level Explainability – A Challenge for Creating Trust in Superhuman AI Strategies

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Abstract
For complex strategic video games, intelligent systems based on Deep Reinforcement Learning (DRL) have demonstrated an impressive ability to learn solutions that can go beyond human capabilities. While this might create new opportunities for the development of assistance systems with groundbreaking functionalities, applying this technology to real-world problems carries significant risks and therefore requires trust and transparency. Compared to other AI systems complex superhuman strategies are non-intuitive and difficult to explain. A representative empirical performance evaluation in real-world scenarios is often impossible. Explainable AI (XAI) has improved the transparency of modern AI systems through a variety of measures, however, research has not yet provided solutions enabling domain-level insights for expert users of DRL systems in strategic situations. In this position paper, we discuss the existence of superhuman DRL-based strategies, their properties, the requirements and challenges for applying them to real-world environments, and the need for explainability at the domain-level as a key ingredient to enable trust.

Introduction
Deep Reinforcement Learning (DRL) is an area of machine learning where the system learns from interacting with the environment and actions are reinforced based on reward values. The algorithms optimize the expected long-term reward and continuously improve their actions and policies. Reward signals are available in many scenarios and often come with lower costs than labels required for supervised methods. This approach can even be used when no clear labeling is possible (Feng et al. 2018). Because DRL only specifies the problem to solve and not the solution, DRL systems have the potential to achieve performance beyond that of domain experts. This superhuman potential makes them interesting in complex and strategic real-world challenges.

In strategic problems, an agent has to achieve a long-term objective through a complex set of highly-significant actions. Such problems are "dynamic, hostile, and smart" (Buro 2003) and share aspects of complexity with video games, such as: decision under uncertainty, spatial and temporal reasoning, and agent collaboration. Strategy (video) games have been used to support real-world (military) training (Herz and Macedonia 2002) and have also proven ideal for the development of DRL AI.

In 2016, AlphaGo (Silver et al. 2016), a Deep Reinforcement Learning (DRL) algorithm, demonstrated a performance that surpassed that of the best human players of Go, a strategy game considered beyond the reach of traditional AI due to its prohibitively large branching factor. One year later, AlphaZero (Silver et al. 2017) proved that an AI can learn a superior Go strategy from the game’s rules alone, without any expert input. Since then, DeepMind’s AlphaStar (Vinyals et al. 2019) and OpenAI Five (Berner et al. 2019) have further advanced the capabilities of DRL systems. This research did not only focus on existing games but introduced flexible game-like environments for general strategic AI research (Tian et al. 2017).

While the research on DRL-based strategies is steadily making progress for complex video games, its transfer to practical real-world applications, where DRL may have a potential for superhuman disruption, is lacking. One reason may be found in low degrees of explainability which counteract human understanding and acceptance. Actions formulated by an assistant system are only implicitly learned, evaluated and encoded in a Deep Neural Network. Resulting strategies cannot be represented with regular planning techniques and explicit explanations are not easily available. We argue new forms of explainability need to be developed.

In this paper, we discuss the potential for superhuman strategies and possible challenges based on our combined experience from industrial and practical uses. From a combination of machine learning, trust, and innovation research we identify domain-level transparency as one of the core difficulties facing AI applications in order to leverage successful superhuman DRL solutions in strategic real-world scenarios and specify approaches to provide explainability.

Potential barriers and challenges
Strategies adopted by DRL agents are similar to disruptive innovation processes in business models (Christensen 2013), as they are able to provide superhuman solutions that challenge established structures and theories. Following the description of innovative business models (Chesbrough 2010), we derive preconditions for superhuman strategic disrup-
Spatial & temporal reasoning: Actions are not only conditioned on the currently “visible” state but also on past and future states. Relevance of observations depends on both state and actions.

Collaboration: Interdependencies between actions of competitors and collaborators are essential in game-theory-like scenarios.

Decision-making under uncertainty: Incomplete and uncertain information plays a major role in determining an optimal strategy.

Resource management: Short term resources must be allocated towards a long-term strategic goal. Measurable advantages may appear long after a decisive action, with results appearing disadvantageous in the mean time.

Opponent modeling & learning: Learning from experience and adapting to scenarios and opponents.

Adversarial real-time planning: Long-time planning may be required due to sparse reward signals.

Huge action- & state-spaces: Some environments have a number of variables, observations, possible actions, or rules that is much larger than in classical strategy games.

Future projections: Analysis of (potential) future states, events, and competitor behavior.

Hypothetical scenarios: Study of “what-if” scenarios on changes/hypothetical/potential future states.

Risk, transparency & safety: Risks due to “real” randomness or uncertain collaborator/competitor behavior.

Uncertainty: Simulation results have to indicate how well the model is likely to capture a given situation (e.g. detection of out-of-distribution cases).

Existence of strategic real-world challenges

Strategic environments with high complexity and high uncertainty have been traditionally tackled with simplified (stochastic) models or scenario planning (Schoemaker et al. 2004). Academic strategic models along with application of game theory to conflict research (Slantchev 2017) and operations research (Forder 1998) began with World War II and grew in popularity during Cold War conflicts. Market competition has since gained a considerable importance (Moorthy 1993) and these methods have proven helpful in price strategy (Andrulis and Ender 2009) and logistics (Cachon and Netessine 2006) problems.

The scope of problems that can be addressed this way is, however, limited: in Table 1, we compile strategic complexity challenges that can be seen in research (Buro 2003) and applications (labeled C1 to C7 in the table). When some of these criteria are met, simplification is required to approach the problem with established strategic planning methods while DRL agents have been shown to master this level of strategic complexity.

For example, OpenAI Five (Berner et al. 2019) is a remarkable case that excels in all those criteria: in DOTA 2, an incomplete information game (C3), teams of five compete against each other (C2) with limited information about the actions of the competitors (C5). Successful moves require coordination and planning (C1), forcing players to adapt and build resources in a long-term effort (C4). In a match, each agent plans up to 80,000 turns with each time up to 170,000 possible actions (C7) while there are no meaningful rewards until a match is either won or lost. OpenAI has been able to build agents that compete successfully against the world’s best DOTA 2 players in real-time competition (C6).

Potential for superhuman disruption

In competitions against world’s best human players, DRL has been able to achieve unexpected and superior results—which we classify as superhuman disruptions. This has even been the case for strategy games that have received the attention of millions of players for decades or even centuries.

In Go, one great example for this is turn 37 of game 2 between AlphaGo (Silver et al. 2016) and Lee Sedol that resulted in the AI’s victory (Holcomb et al. 2018).

“During the games, AlphaGo played several inventive winning moves, several of which – including move 37 in game two – were so surprising that they upended hundreds of years of wisdom. Players of all levels have extensively examined these moves ever since.”

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complexity of real-world scenarios – with one of the world’s best players stating after losing against OpenAI Five:

“It did things that we had never seen anybody else do and it has set a type of play style that we pretty much just copy now. When I see the bot make a play, it clicks in my head. I’m like, ‘why aren’t we doing that?’”

The existence of superhuman disruptive results for any given problem can never be guaranteed. We argue, however, that experience with complex games has shown that we can expect superhuman disruptions in real applications as well. The reason for the lack of superhuman DRL in real-world scenarios cannot be attributed to a lack of potential.

**Trust in superhuman AI-strategies**

Even if technical challenges can be solved, trust is essential in practical AI applications (Ferrario, Loi, and Viganò 2019), as safety requirements and threats can lead to economic costs, risks, and even regulatory issues. A human expert has to make the decision to delegate to the AI some aspect of importance in achieving a goal without the possibility to completely verify the AI’s suggestion and all its potential implications (Grodzinsky et al. 2011).

Four key components have been shown to build trust in AI: transparency, reliability, tangibility and task characteristics (Glikson and Woolley 2020). Of those four, transparency and reliability do not depend on the specific system. They can be the basis for general machine learning requirements and correspond to the technically researched areas of robustness and explainability. Both define a trusted zone shown on Figure 1.

This Figure illustrate that trust might be obtained for robust and not explainable models, or explainable but not robust ones, while higher trust is achieved for models that are both robust and explainable.

**Robustness:** Robustness is a concept developed in control theory (Sastry and Bodson 2011), which is intended for dealing with the effects of uncertainties. This idea has been applied to machine learning models by measuring the impact of fluctuating inputs or environments such as uncertainties coming from modeling errors (Reinelt, Garulli, and Ljung 2002), poor generalization due to overfitting, or intentional adversarial attacks. Robustness is an ongoing challenge for DRL. It has been very difficult to build generalizing DRL agents (Colbe et al. 2019) with recent success only for simple environments (Badia et al. 2020) and, for some DRL models, even naively executed adversarial attacks can have a significant impact on performance (Pattanaik et al. 2017). Seemingly unimportant changes in hyperparameters or the random seed can also produce drastically different results (Henderson et al. 2017). Given these issues with robustness, one way to satisfy safety concerns is through the integration of safety constraints (Junges et al. 2016; Cheng et al. 2019). Overall, research in this area is still active and currently represents a major challenge in the development of DRL systems.

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2William “BlitzDota” Lee on OpenAI Five playing DOTA 2.
economy options. This kind of XAI output - which is especially useful for domain experts without any further AI knowledge - can be found in three of thirteen papers they reviewed: (Madumal et al. 2019; Sequeira and Gervasio 2019; van der Waa et al. 2018).

As key finding, they conclude that the ability to not only extract or generate explanations for the decisions of the model, but also to present this information in a way that is understandable by human (non-expert) users, makes it possible to predict the behaviour of a model. This definition of XAI implicitly assumes that the expert perfectly understands the strategic problem and can easily judge the right action. In a domain of high complexity and uncertainty, where intuitive judgment should not be trusted (Hogarth 2001), this cannot be easily expected and strategic explanations become a key challenge – making AlphaGo’s turn 37 in game 2 predictable through XAI is a far greater challenge than the examples the authors had in mind.

Summary: Trust is an essential factor for the deployment and leveraging of DRL systems in real-world scenarios. Both current robustness and explainability methods are not suited for the requirements of complex strategic environments and constitute areas where further research is required.

Domain-Level XAI

Considering the limits for XAI in strategy contexts, discussed in the last section, one may ask: What are the key ingredients for a ‘strategic’ XAI that will help human experts learn from superhuman AIs? This question cannot be answered on a technical level alone but must also address the strategic complexity (C1–C7) in a way that a domain expert with no machine learning mastery can use this information.

To achieve this, established tools for scenario planning (Schoemaker et al. 2004) can be adopted and translated into requirements for ‘strategic explainability’ in a DRL context (E1–E4 in Table 1). While scenario planning is limited and mostly qualitative, its approach to uncertainty (Courtney, Kirkland, and Viguerie 1997) and the criteria for scenario selection provide solid foundations for strategic explainability of DRL-AI results.

The main questions and drivers for scenarios are predictions of the future (E1) and the impact of changes in hypothetical scenarios (E2). While classical scenario planning has no way of quantify probability distributions, DRL adds this quantitative dimension with the potential to add a measure for risk (E3) and model uncertainty (E4).

Transparency of superhuman AI-strategies is essential and future research must further focus on domain-level explainability (E1–E4) in strategically complex environments (C1–C7). Established approaches to strategy modeling, such as scenario planning, may be a great resource for building strategic AI-assistant systems and gaining the trust of experts in the potential for superhuman disruptions.

Conclusion & Future Work

There are real-world strategic use-cases that offer great potential for superhuman innovation through the use of DRL-AIs. Because the robustness of complex real-world strategies often cannot be empirically validated, trust in these systems must be built through transparency and explainability. Current XAI methods cannot offer the domain-level strategy explanations that are necessary for an expert to understand counter-intuitive superhuman strategies (Hogarth 2001). In order to build trust-enabling transparency into strategy AIs, the current concepts of explainability need to be enhanced. The implicitly learned strategic complexity requires an explainability that can address concepts beyond the relationship of individual input and output combinations for users without technical machine learning knowledge. Those need to be implemented as readily available tools that can be applied to AI agents. Finally, future studies will have to show that domain-level strategic explainability is possible so that human experts can trust and benefit from superhuman strategies issued by a DRL-AI in real-world applications.

References

Andrulis, J., and Ender, M. 2009. Strategic retail banking competition in distributed markets with varying switching costs. In Quantitative Methods in Finance Conference.

Bach et al. 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS one 10(7):e0130140.

Badia et al. 2020. Agent57: Outperforming the Atari Human Benchmark. arXiv:2003.13350.

Berner et al. 2019. Dota 2 with Large Scale Deep Reinforcement Learning. arXiv:1912.06680.

Buro, M. 2003. Real-time strategy games: A new AI research challenge. In IJCAI, volume 2003, 1534–1535.

Cachon, G. P., and Netessine, S. 2006. Game theory in supply chain analysis. In Models, methods, and applications for innovative decision making. INFORMS. 200–233.
Cheng et al. 2019. End-to-end safe reinforcement learning through barrier functions for safety-critical continuous control tasks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, 3387–3395.

Chesbrough, H. 2010. Business model innovation: opportunities and barriers. *Long range planning* 43(2-3):354–363.

Christensen, C. M. 2013. *The innovator’s dilemma: when new technologies cause great firms to fail*. Harvard Business Review Press.

Cobbe et al. 2019. Quantifying generalization in reinforcement learning. In *International Conference on Machine Learning*, 1282–1289.

Courtney, H.; Kirkland, J.; and Viguerie, P. 1997. Strategy under uncertainty. *Harvard business review* 75(6):67–79.

Craven, M., and Shavlik, J. W. 1996. Extracting tree-structured representations of trained networks. In *Advances in neural information processing systems*, 24–30.

Du, M.; Liu, N.; and Hu, X. 2019. Techniques for interpretable machine learning. *Communications of the ACM* 63(1):68–77.

Feng et al. 2018. Reinforcement learning for relation classification from noisy data. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

Ferrario, A.; Loi, M.; and Viganò, E. 2019. In *AI We Trust Incrementally: a Multi-layer Model of Trust to Analyze Human-Artificial Intelligence Interactions*. *Philosophy and Technology*.

Fong, R. C., and Vedaldi, A. 2017. Interpretable explanations of black boxes by meaningful perturbation. In *Proceedings of the IEEE International Conference on Computer Vision*, 3429–3437.

Forder, R. A. 1998. Military Operations Research: Quantitative Decision Making. *Journal of the Operational Research Society* 49(11):1227–1228.

Friedman, J. H. 2001. Greedy function approximation: a gradient boosting machine. *Annals of statistics* 1189–1232.

Frohlich et al. 2011. Developing artificial agents worthy of trust:“would you buy a used car from this artificial agent?”. *Ethics and information technology* 13(1):17–27.

Guidotti et al. 2018. A survey of methods for explaining black box models. *ACM computing surveys (CSUR)* 51(5):1–42.

Hein, D.; Udluft, S.; and Runkler, T. A. 2018. Interpretable policies for reinforcement learning by genetic programming. *Engineering Applications of Artificial Intelligence* 76:158–169.

Henderson et al. 2017. Deep Reinforcement Learning that Matters. *arXiv:1709.06560*.

Herz, J., and Macedonia, M. R. 2002. *Computer Games and the Military: Two Views*. Center for Technology and National Security Policy, National Defense University.

Hogarth, R. M. 2001. *Educating intuition*. University of Chicago Press.

Holcomb et al. 2018. Overview on DeepMind and Its AlphaGo Zero AI. In *Proceedings of the 2018 International Conference on Big Data and Education*, ICBDE ’18, 67–71. New York, NY, USA: Association for Computing Machinery.

Johansson, U., and Niklasson, L. 2009. Evolving decision trees using oracle guides. In *2009 IEEE Symposium on Computational Intelligence and Data Mining*, 238–244. IEEE.

Junges et al. 2016. Safety-constrained reinforcement learning for MDPs. In *International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, 130–146. Springer.

Lage et al. 2019. An evaluation of the human-interpretability of explanation. *arXiv:1902.00006*.

Liu et al. 2018. Toward interpretable deep reinforcement learning with linear model u-trees. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 414–429. Springer.

Madumal et al. 2019. Explainable reinforcement learning through a causal lens. *arXiv:1905.10958*.

Moorthy, K. S. 1993. Competitive marketing strategies: Game-theoretic models. *Handbooks in operations research and management science* 5:143–190.

Pattanaik et al. 2017. Robust deep reinforcement learning with adversarial attacks. *arXiv:1712.03632*.

Puiutta, E., and Veith, E. 2020. Explainable Reinforcement Learning: A Survey. *arXiv:2005.06247*.

Reinelt, W.; Garulli, A.; and Ljung, L. 2002. Comparing different approaches to model error modeling in robust identification. *Automatica* 38(5):787–803.

Ribiero, M. T.; Singh, S.; and Guestrin, C. 2016. Why should I trust you?: Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 1135–1144. ACM.

Saltelli, A. 2002. Sensitivity analysis for importance assessment. *Risk analysis* 22(3):579–590.

Sastry, S., and Bodson, M. 2011. *Adaptive Control: Stability, Convergence and Robustness*. Courier Corporation.

Schoemaker et al. 2004. Forecasting and scenario planning: the challenges of uncertainty and complexity. *Handbook of judgment and decision-making*, eds., DJ Koehler and N. Harvey. Oxford, UK: Blackwell 274–296.

Sequeira, P., and Gervasio, M. 2019. Interestingness Elements for Explainable Reinforcement Learning: Understanding Agents’ Capabilities and Limitations. *arXiv:1912.09007*.

Silver et al. 2016. Mastering the game of Go with deep neural networks and tree search. *Nature* 529(7587):484–489.

Silver et al. 2017. Mastering the game of Go without human knowledge. *Nature* 550(7676):354–359.

Slantchev, B. L. 2017. On the Proper Use of Game-Theoretic Models in Conflict Studies. *Peace Economics, Peace Science and Public Policy* 23(4).

Tian et al. 2017. ELF: An extensive, lightweight and flexible research platform for real-time strategy games. In *Advances in Neural Information Processing Systems*, 2659–2669.

van der Waa et al. 2018. Contrastive explanations with local foil trees. *arXiv:1806.07470*.

Verma et al. 2018. Programmatically interpretable reinforcement learning. *arXiv:1804.02477*.

Vinyals et al. 2019. Grandmaster level in StarCraft II using multi-agent reinforcement learning. *Nature* 575(7782):350–354.

Xu et al. 2015. Show, attend and tell: Neural image caption generation with visual attention. In *International conference on machine learning*, 2048–2057.

Yosinski et al. 2015. Understanding neural networks through deep visualization. *arXiv:1506.06579*.