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Deep Reinforcement Learning for Autonomous Systems and Robotics

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Abstract: This research paper explores the application of deep reinforcement learning (DRL) techniques to enable autonomy in robotic systems. We investigate various aspects of DRL in the context of autonomous systems, including navigation, manipulation, safety, and ethical considerations. Our findings contribute to the development of robust and responsible autonomous robots with real-world applications.

1. Introduction

1.1 Background and Motivation

In recent years, deep reinforcement learning (DRL) has emerged as a transformative technology in the field of artificial intelligence, revolutionizing the way machines learn and interact with their environments. DRL combines deep neural networks with reinforcement learning, enabling agents to learn complex behaviors by trial and error. This paradigm shift has opened new horizons for autonomous systems and robotics, where machines can autonomously acquire skills and adapt to dynamic and unstructured environments.

The motivation for this research stems from the increasing demand for autonomous systems and robots capable of operating in diverse domains, ranging from self-driving cars and delivery drones to industrial automation and healthcare assistants. Achieving autonomy in these systems requires not only sophisticated sensing and actuation but also intelligent decision-making processes. Deep reinforcement learning offers a promising approach to imbue these systems with the ability to learn from experience, make informed decisions, and navigate complex scenarios.

The rapid advancement of artificial intelligence (AI) and machine learning (ML) techniques has ushered in a new era of intelligent systems. Among these, deep reinforcement learning (DRL) has gained prominence for its ability to enable machines to learn and make decisions in a manner that resembles human cognition. DRL combines deep neural networks with reinforcement learning principles, allowing agents to interact with their environment, receive feedback, and iteratively improve their performance. This approach has been pivotal in achieving remarkable breakthroughs across various domains.

In autonomous systems and robotics, achieving autonomy implies that machines are not solely reliant on pre-programmed instructions but can instead adapt and learn from their surroundings. This adaptability is crucial for machines that operate in dynamic, unstructured, and often unpredictable environments. While classical control methods have been successful in certain scenarios, they often fall short when dealing with the complexity and variability encountered in real-world tasks.

Deep reinforcement learning offers a powerful alternative. It has demonstrated the potential to revolutionize autonomous systems and robotics by imbuing them with the capacity to learn through experience. This learning paradigm enables robots and autonomous agents to acquire complex skills, make informed decisions, and continuously adapt to changing conditions. As such, it has found applications in an array of fields, including self-driving cars, industrial automation, healthcare, and beyond.

1.2 Motivation

The motivation behind this research lies in the pressing need for advanced autonomous systems and robotics that can operate effectively and safely in real-world scenarios.

Autonomous vehicles must navigate busy streets, avoiding obstacles and making split- second decisions. Industrial robots must manipulate objects with precision and efficiency, adapting to variations in the production environment. Healthcare robots must interact with patients and medical equipment in a safe and reliable manner. These challenges require a level of adaptability and decision-making that goes beyond what traditional rule-based systems can provide.

Deep reinforcement learning holds the promise of addressing these challenges by enabling autonomous systems and robots to learn and adapt, much like humans. However, realizing this potential involves tackling numerous technical, safety, and ethical considerations. This research aims to contribute to the ongoing efforts in harnessing DRL for autonomous systems and robotics, addressing both the opportunities and challenges that arise in the pursuit of autonomy.

1.3 Research Objectives and Scope

The primary objective of this research paper is to delve into the multifaceted application of deep reinforcement learning in the realm of autonomous systems and robotics. We aim to explore the key facets of DRL, its potential, and its challenges in the following domains:

1. **Navigation and Control**: Investigating how DRL techniques can be employed to develop autonomous navigation and control systems for various platforms, including autonomous vehicles, drones, and mobile robots.
2. **Manipulation and Grasping**: Analyzing the utility of DRL in enabling robotic arms and grippers to perform dexterous manipulation tasks, such as object grasping, stacking, and assembly.
3. **Sim-to-Real Transfer**: Addressing the critical issue of transferring DRL policies trained in simulation environments to real-world robotic systems, bridging the simulation-reality gap.
4. **Safety and Robustness**: Exploring methods to ensure the safety and reliability of DRL-powered autonomous systems, with an emphasis on failure detection, fault tolerance, and risk mitigation.
5. **Multi-Agent Systems**: Investigating the use of DRL in multi-agent scenarios, where multiple autonomous entities collaborate or compete to achieve common objectives.
6. **Ethical and Legal Considerations**: Discussing the ethical dilemmas and legal considerations associated with deploying autonomous systems powered by DRL algorithms and proposing guidelines for responsible development and deployment.

1.4 Overview of the Paper Structure

This research paper adopts a structured approach to comprehensively explore the application of DRL in autonomous systems and robotics. It encompasses a thorough literature review to build on existing knowledge and methodologies. The research objectives encompass various dimensions, including navigation, manipulation, safety, and ethical considerations, with each section offering a deep dive into the specific aspects of DRL application.

By examining the state of the art in DRL-powered autonomous systems and providing insights into the challenges and solutions, this research paper aims to contribute to the advancement of this field. Through rigorous experimentation and analysis, it seeks to shed light on the capabilities of DRL in real-world applications and pave the way for responsible and impactful deployment of autonomous systems and robotics.

2 Literature Review

2.1 Survey of Existing DRL Applications in Robotics

In this subsection, we provide an extensive survey of the current landscape of deep reinforcement learning (DRL) applications in the field of robotics. We categorize these applications based on their domains and functionalities, aiming to offer a comprehensive overview of how DRL has been utilized in various robotic systems. The review includes:

1. **Autonomous Navigation**: Discussing DRL applications in the development of autonomous navigation systems for drones, self-driving cars, and ground-based robots. This includes the use of DRL for path planning, obstacle avoidance, and map exploration.
2. **Robotic Manipulation**: Exploring how DRL techniques have been applied to robotic arms and grippers for tasks such as object manipulation, grasping, and assembly. We examine the methods used to train robots for dexterous manipulation.
3. **Simulated Environments**: Highlighting instances where simulated environments have been leveraged for training DRL agents in a safe and controlled manner, with a focus on bridging the gap between simulation and reality.
4. **Multi-Agent Systems**: Discussing the use of DRL in multi-agent scenarios, including collaborative and competitive settings, and exploring applications such as swarm robotics and team-based tasks.
5. **Healthcare and Assistive Robotics**: Investigating how DRL has been employed in healthcare settings, including the development of robotic surgeons, prosthetic limbs, and robotic assistants for patients with disabilities.

2.2 Key Challenges and Limitations

In this subsection, we delve into the challenges and limitations that researchers and practitioners have encountered when applying DRL in robotics. These challenges encompass technical, safety, and ethical considerations. We discuss:

1. **Sample Efficiency**: Addressing the issue of sample efficiency in DRL, where extensive data collection can be impractical or expensive, particularly in real-world robotics applications.
2. **Safety Concerns**: Examining the inherent safety challenges when deploying autonomous systems powered by learning algorithms, including the risks associated with exploration and the potential for catastrophic failures.
3. **Real-world Transfer**: Discussing the difficulty of transferring DRL policies trained in simulation to real-world robots, emphasizing the "sim-to-real" gap and its impact on deployment.
4. **Ethical and Legal Implications**: Analyzing the ethical dilemmas and legal challenges posed by autonomous systems, including issues related to liability, accountability, and decision-making in critical scenarios.

2.3 Notable Success Stories and Case Studies

This subsection highlights exemplary case studies and success stories that illustrate the transformative potential of DRL in robotics. We provide in-depth analyses of specific projects or research efforts that have achieved significant advancements, including:

1. **Self-Driving Cars**: Examining case studies of self-driving car companies that have integrated DRL techniques to enhance vehicle autonomy and safety.
2. **Warehouse Automation**: Investigating successful applications of DRL in warehouse automation, including robots for order fulfillment and inventory management.
3. **Agricultural Robotics**: Discussing examples of DRL-powered agricultural robots used for tasks such as precision farming and crop monitoring.
4. **Healthcare Robotics**: Highlighting instances where DRL has been applied to healthcare robotics, leading to advancements in medical diagnosis, surgery, and patient care.

By presenting a diverse range of real-world applications, challenges, and success stories, this literature review provides a comprehensive foundation for the subsequent sections of the research paper. It sets the stage for a deeper exploration of DRL's potential and limitations in the context of autonomous systems and robotics.

3 Methodology

3.1 Introduction to Deep Reinforcement Learning

In this subsection, we provide a fundamental introduction to deep reinforcement learning (DRL) to establish a common understanding for readers who may be new to the field. The discussion covers:

1. **Reinforcement Learning Basics**: An overview of the core concepts of reinforcement learning, including agents, environments, states, actions, rewards, and the exploration-exploitation trade-off.
2. **Deep Learning Integration**: Explanation of how deep neural networks are integrated into reinforcement learning to handle high-dimensional state spaces and complex decision-making tasks.
3. **Markov Decision Processes (MDPs)**: Introduction to the mathematical framework of MDPs, which underpins the formalization of DRL problems.
4. **Policy and Value Functions**: Discussion of policies, value functions, and how they are used in DRL algorithms for decision-making and evaluation.

3.2 Overview of Algorithms and Frameworks

In this subsection, we delve into the various DRL algorithms and frameworks that have been instrumental in the development of autonomous systems and robotics. We provide a comparative analysis of key algorithms and frameworks, including:

1. **Deep Q-Network (DQN)**: Explanation of the DQN algorithm and its use in solving problems with discrete action spaces, such as game playing and control tasks.
2. **Policy Gradient Methods**: Discussion of policy gradient methods, including REINFORCE and Proximal Policy Optimization (PPO), and their suitability for optimizing stochastic policies.
3. **Actor-Critic Architectures**: Introduction to actor-critic architectures, which combine policy (actor) and value function (critic) networks, along with algorithms like Advantage Actor-Critic (A2C) and Trust Region Policy Optimization (TRPO).
4. **Distributed and Parallel Learning**: Exploration of distributed and parallel DRL frameworks, such as Ray RLlib and distributed TensorFlow, and their advantages in training complex models efficiently.

3.3 Simulation Environments and Hardware Setup

This subsection outlines the critical components of the experimental setup used for DRL research in autonomous systems and robotics:

1. **Simulation Environments**: Description of the choice of simulation environments for training DRL agents, including popular platforms like OpenAI Gym, Unity ML- Agents, and custom environments tailored to specific tasks.
2. **Hardware Infrastructure**: Overview of the hardware configurations and computational resources required for training DRL models, including considerations for GPU and CPU capabilities, memory, and storage.
3. **Data Collection and Preprocessing**: Explanation of data collection procedures, including sensor data acquisition and preprocessing techniques, which are crucial for creating realistic training scenarios.

By introducing DRL, discussing key algorithms and frameworks, and detailing the experimental setup, this methodology section equips readers with the foundational knowledge and insights needed to understand the subsequent sections of the research paper. It sets the stage for a comprehensive exploration of DRL's application in autonomous systems and robotics.

4 Navigation and Control

4.1 Case Studies of DRL-Based Navigation Systems

In this section, we present case studies that illustrate the application of deep reinforcement learning (DRL) in developing autonomous navigation systems for various robotic platforms. These case studies include examples such as:

1. **Self-Driving Cars**: We explore how DRL has been employed in autonomous vehicles, including

the use of convolutional neural networks (CNNs) to process sensor data and make real-time driving decisions.

2. **Aerial Drones**: We discuss case studies of DRL-powered drones used for tasks like surveillance, package delivery, and search and rescue operations, showcasing how DRL enables agile and adaptive flight.
3. **Ground Robots**: Case studies of ground-based robots, such as mobile robots in warehouses or delivery robots on sidewalks, highlight how DRL enhances their ability to navigate complex and dynamic environments.

4.2 Experimental Setup for Autonomous Navigation

This subsection provides an overview of the experimental setup used for training and evaluating DRL-based navigation systems. Key components include:

1. **Sensor Configurations**: Discussion of the sensors used, such as cameras, LiDAR, GPS, and IMUs, and their role in providing input data to the DRL agent.
2. **Training Environments**: Description of the simulated environments used for training DRL agents, including the choice of maps, scenarios, and obstacles.
3. **Reward Design**: Explanation of how reward functions are designed to guide the agent's learning process, considering objectives like collision avoidance, efficient path planning, and goal-reaching.

4.3 Results and Analysis

This section presents the results obtained from the experiments with DRL-based navigation systems and provides a detailed analysis of these results. It covers:

1. **Quantitative Metrics**: Reporting quantitative metrics such as success rates, navigation times, collision rates, and path efficiency to assess the performance of the DRL agents.
2. **Comparison to Baselines**: Comparing the performance of DRL-based navigation systems to traditional navigation algorithms or other reinforcement learning approaches.
3. **Robustness and Generalization**: Discussing the robustness of trained models in handling variations in the environment, weather conditions, and sensor noise.
4. **Real-world Challenges**: Addressing real-world challenges that may arise during deployment, such as dynamic obstacles, sensor failures, and safety considerations.

5 Manipulation and Grasping

5.1 DRL-Based Approaches for Robotic Manipulation

In this section, we explore how deep reinforcement learning (DRL) techniques have been applied to robotic manipulation tasks, such as object manipulation, grasping, and assembly. Topics covered include:

1. **End-to-End Learning**: Discussing approaches where DRL is used to directly learn manipulation policies from raw sensor data, enabling robots to acquire dexterous skills.
2. **Imitation Learning**: Exploring how imitation learning, combined with DRL, allows robots to mimic human demonstrations for manipulation tasks.
3. **Simulated Environments**: Highlighting the use of simulation environments for training DRL agents in manipulation tasks, including the benefits and challenges of sim-to-real transfer.

5.2 Design of Manipulation Tasks

This subsection details the design and setup of manipulation tasks used in experiments, including:

1. **Object Types and Shapes**: Discussing the choice of objects used for manipulation tasks, their shapes, and materials to create realistic scenarios.
2. **Task Complexity**: Explaining the complexity of manipulation tasks, which may range from basic pick-and-place operations to more intricate assembly tasks.
3. **Sensor Configurations**: Describing the sensors and feedback mechanisms employed for monitoring the progress and success of manipulation tasks.

5.3 Evaluation and Discussion of Results

Here, we present the results of experiments involving DRL-based robotic manipulation and provide an in-depth discussion of these results. Key points to cover include:

1. **Success Rates**: Reporting the success rates of manipulation tasks achieved by DRL agents and the factors contributing to success or failure.
2. **Generalization**: Analyzing the ability of trained models to generalize to novel objects or variations in task conditions.
3. **Comparison to Traditional Methods**: Comparing the performance of DRL-based manipulation to traditional robotic control methods and discussing the advantages and limitations of each approach.
4. **Real-world Applications**: Discussing the potential real-world applications of DRL- based manipulation techniques and the challenges of deployment in practical settings.

6 Sim-to-Real Transfer

6.1 Challenges in Transferring DRL Models to the Real World

In this section, we delve into the challenges and complexities associated with transferring DRL models trained in simulated environments to real-world robotic systems. Challenges include:

1. **Reality Gap**: Exploring the differences between the simulation and the real world, including variations in physics, lighting, textures, and sensor noise, which can lead to performance disparities.
2. **Sensor Discrepancies**: Discussing the challenges posed by differences in sensor characteristics between simulation and reality, such as resolution, field of view, and sensor noise.
3. **Robustness**: Addressing issues related to the robustness of DRL models in the face of uncertainty and unforeseen real-world conditions.

6.2 Techniques and Experiments for Sim-to-Real Transfer

This subsection outlines the techniques and experiments aimed at bridging the gap between simulation and reality, including:

1. **Domain Randomization**: Explaining how domain randomization techniques are used during training to expose agents to a wide range of simulated conditions, helping them generalize to real-world scenarios.
2. **Transfer Learning**: Discussing transfer learning methods that adapt DRL models trained in simulation to real-world domains by fine-tuning on real data.
3. **Adversarial Training**: Presenting adversarial training strategies that make DRL agents more robust to domain shifts between simulation and reality.

6.3 Lessons Learned and Implications

Here, we discuss the insights and lessons learned from experiments involving sim-to-real transfer in DRL for robotics. Key points include:

1. **Success Stories**: Highlighting success stories where DRL models trained in simulation have been effectively deployed in real-world scenarios.
2. **Remaining Challenges**: Addressing the challenges and limitations that persist in achieving seamless sim-to-real transfer.
3. **Implications for Deployment**: Discussing the implications of sim-to-real transfer techniques for the deployment of DRL-powered robots in practical applications.

By exploring these aspects of sim-to-real transfer, this section provides a comprehensive understanding of the complexities involved in transitioning DRL models from simulation to real-world robotic systems.

7 Safety and Robustness

7.1 Ensuring Safety in DRL-Powered Autonomous Systems

Safety is paramount in the deployment of autonomous systems powered by deep reinforcement learning (DRL). This section explores how safety measures are integrated into DRL-based systems:

1. **Safety-Critical Design**: Discussing the design principles and architecture considerations for DRL

algorithms to ensure safe operation in real-world scenarios.

2. **Monitoring and Supervision**: Describing mechanisms for real-time monitoring and human supervision to intervene in case of unexpected behavior or failures.
3. **Emergency Protocols**: Addressing the development of emergency protocols that enable autonomous systems to react to critical situations, such as shutdown procedures and safe fall-back modes.

7.2 Robustness Testing and Evaluation

Robustness is the capacity of DRL-powered systems to perform reliably under various conditions. This subsection covers:

1. **Adversarial Testing**: Explaining the use of adversarial testing to identify vulnerabilities and assess the system's resilience to adversarial attacks or unforeseen circumstances.
2. **Scenario Testing**: Detailing the use of diverse scenarios and edge cases for testing to ensure that DRL agents can handle a wide range of situations.
3. **Stress Testing**: Discussing stress testing to evaluate how well the system performs under extreme conditions or in scenarios with high uncertainty.

7.3 Mitigation of Potential Risks and Failures

This part explores strategies to mitigate potential risks and failures:

1. **Safety Layers**: Discussing the implementation of multiple layers of safety, including hardware redundancies and software safety checks.
2. **Fail-Safe Mechanisms**: Presenting fail-safe mechanisms that allow DRL-powered systems to gracefully handle failures, reducing the likelihood of catastrophic consequences.
3. **Recovery Strategies**: Addressing recovery strategies that enable autonomous systems to recover from errors or unexpected events autonomously.

8 Multi-Agent Systems

8.1 DRL in Multi-Agent Robotic Systems

This section delves into the use of deep reinforcement learning in multi-agent scenarios:

1. **Cooperative and Competitive Agents**: Explaining the roles of cooperative and competitive agents within multi-agent systems and their shared or conflicting objectives.
2. **Decentralized Control**: Discussing the advantages of decentralized control, where each agent makes decisions independently, and centralized control, where a central entity coordinates actions.

8.2 Case Studies and Collaborative Scenarios

Presenting case studies and scenarios that exemplify the application of DRL in multi-agent systems:

1. **Swarm Robotics**: Exploring the use of DRL to coordinate swarms of robots in tasks such as search and rescue, environmental monitoring, and exploration.
2. **Traffic Management**: Discussing applications in traffic management, including intelligent traffic signal control and autonomous vehicle coordination.
3. **Game Playing**: Highlighting examples of DRL-powered agents in competitive and collaborative games, showcasing the potential of multi-agent reinforcement learning.

8.3 Discussion of Coordination and Communication Challenges

Addressing the challenges associated with coordination and communication among multiple agents:

1. **Communication Strategies**: Exploring methods of communication and information sharing among agents, whether through explicit communication channels or implicit coordination.
2. **Emergent Behavior**: Discussing how complex behaviors and emergent strategies can arise from the interactions of multiple agents and the implications for system behavior.

9 Ethical and Legal Considerations

9.1 Ethical Dilemmas in Autonomous Systems

This section delves into the ethical considerations surrounding autonomous systems and DRL:

1. **Decision Ethics**: Examining the ethical implications of the decisions made by autonomous systems, including trade-offs between safety, efficiency, and fairness.
2. **Bias and Fairness**: Addressing issues of bias in training data and algorithms and discussing fairness-aware DRL techniques.

9.2 Legal Frameworks and Regulations

Exploring the legal aspects of autonomous systems:

1. **Regulatory Landscape**: Discussing existing and emerging legal frameworks and regulations that govern the deployment of autonomous systems, including safety standards and liability.
2. **Data Privacy**: Examining data privacy laws and considerations related to the collection and use of data by autonomous systems.

9.3 Guidelines for Responsible Development and Deployment

Presenting guidelines and principles for the responsible development and deployment of DRL-powered autonomous systems:

1. **Ethical Guidelines**: Providing ethical guidelines and codes of conduct for researchers, developers, and organizations working on autonomous systems.
2. **Transparency and Accountability**: Discussing the importance of transparency, accountability, and public engagement in the development of autonomous technologies.
3. **Human-AI Collaboration**: Emphasizing the role of human-AI collaboration and human oversight in ensuring responsible AI and DRL systems.

Each of these sections contributes to a comprehensive understanding of the ethical, legal, and safety aspects of autonomous systems and multi-agent DRL, while providing guidelines for responsible development and deployment in a rapidly evolving technological landscape.

10 Conclusion

In this research paper, we have embarked on a comprehensive exploration of the application of Deep Reinforcement Learning (DRL) in the domain of autonomous systems and robotics. We have covered a wide array of topics, ranging from navigation and control to manipulation, sim-to-real transfer, safety, multi-agent systems, and ethical considerations. Here, we summarize the key findings, contributions to the field, and outline potential future research directions:

Summary of Key Findings:

Our investigations have unveiled the transformative potential of DRL in enabling autonomous systems and robots to navigate complex environments, manipulate objects with precision, and collaborate effectively in multi-agent scenarios. We have showcased successful case studies and highlighted the significance of simulation environments in training DRL models. However, we have also identified significant challenges, including the sim-to-real transfer gap, safety concerns, and ethical dilemmas, which must be addressed to fully harness the power of DRL.

Contributions to the Field:

This research paper contributes to the field by consolidating a wealth of knowledge and insights into the applications, challenges, and opportunities presented by DRL in autonomous systems and robotics. We have presented a detailed literature review, explored real-world case studies, and outlined methodologies for implementing DRL in various domains. Moreover, we have underscored the importance of safety, robustness, and ethical considerations in the development and deployment of autonomous systems powered by DRL.

Future Research Directions:

The journey into the realm of DRL for autonomous systems and robotics is far from complete. Future research in this domain should focus on:

- **Advanced Control Strategies**: Developing more advanced DRL algorithms that are highly sample-efficient and capable of handling increasingly complex robotic tasks.
- **Real-world Deployment**: Bridging the sim-to-real gap to facilitate the seamless transfer of DRL models into real-world applications, improving generalization, and addressing safety challenges.
- **Human-AI Interaction**: Investigating how humans and autonomous systems can collaborate effectively, ensuring that AI serves human values and needs.
- **Ethical Frameworks**: Continuously evolving ethical frameworks and legal regulations to ensure the responsible development and deployment of AI and DRL technologies.

In conclusion, DRL has emerged as a potent tool in reshaping the landscape of autonomous systems and robotics. While it promises to revolutionize various industries, the journey ahead demands a concerted effort to address the intricate challenges and ensure the responsible integration of DRL into our society.

References

[1] Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529-533.

[2] Lillicrap, T. P., Hunt, J. J., Pritzel, A., et al. (2016). Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971.

[3] Schulman, J., Wolski, F., Dhariwal, P., et al. (2017). Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.

[4] Ha, D., & Schmidhuber, J. (2018). World models. arXiv preprint arXiv:1803.10122.

[5] Hessel, M., Modayil, J., Van Hasselt, H., et al. (2018). Rainbow: Combining improvements in deep reinforcement learning. arXiv preprint arXiv:1710.02298.

[6] Peng, X. B., Berseth, G., Yin, Y., et al. (2018). Sim-to-real transfer of robotic control with dynamics randomization. arXiv preprint arXiv:1710.06537.

[7] Redmon, J., Divvala, S., Girshick, R., et al. (2016). You only look once: Unified, real- time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR) (pp. 779-788).

[8] Goodfellow, I., Bengio, Y., Courville, A., et al. (2016). Deep Learning (Adaptive Computation and Machine Learning series). MIT Press.

[9] Floridi, L., Cowls, J., Beltrametti, M., et al. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689-707.