Deep Reinforcement Learning: Opportunities and Challenges

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Abstract

This article is a gentle discussion about the field of reinforcement learning for real life, about opportunities and challenges, with perspectives and without technical details, touching a broad range of topics. The article is based on both historical and recent research papers, surveys, tutorials, talks, blogs, and books. Various groups of readers, like researchers, engineers, students, managers, investors, officers, and people wanting to know more about the field, may find the article interesting.

In this article, we first give a brief introduction to reinforcement learning (RL), and its relationship with deep learning, machine learning and AI. Then we discuss opportunities of RL, in particular, applications in products and services, games, recommender systems, robotics, transportation, economics and finance, healthcare, education, combinatorial optimization, computer systems, and science and engineering. The we discuss challenges, in particular, 1) foundation, 2) representation, 3) reward, 4) model, simulation, planning, and benchmarks, 5) learning to learn a.k.a. meta-learning, 6) off-policy/offline learning, 7) software development and deployment, 8) business perspectives, and 9) more challenges. We conclude with a discussion, attempting to answer: “Why has RL not been widely adopted in practice yet?” and “When is RL helpful?”.

1 Introduction

There are more and more exciting AI achievements like AlphaGo [Littman et al., 2021]. Deep learning and reinforcement learning are underlying techniques. Besides games, reinforcement learning has been making tremendous progress in diverse areas like recommender systems and robotics. These successes have sparked rapidly growing interests in using reinforcement learning to solve many other real life problems.

Reinforcement learning (RL) refers to the general problem of learning a behavior that optimizes long-term performance metric in a sequential setting. RL techniques can be used to tackle goal-directed or optimization problems that can be transformed into sequential decision making problems. As such, RL overlaps largely with operations research and optimal control, with strong ties to optimization, statistics, game theory, causal inference, sequential experimentation, etc., and applicable broadly to many problems in science, engineering and
The integration of RL and neural networks has a long history, see e.g., Sutton and Barto (2018); Bertsekas and Tsitsiklis (1996); Schmidhuber (2015), with a prominent example in Backgammon (Tesauro, 1994). With recent exciting achievements in deep learning (LeCun et al., 2015; Bengio et al., 2021a), benefiting from big data, powerful computation, new algorithmic techniques, mature software packages and architectures, and strong financial support, we have been witnessing the renaissance of RL (Krakovski, 2016), especially the combination of DL and RL, i.e., deep reinforcement learning (deep RL) (Li, 2017).

Silver (2020) presents the following conjectures. Reinforcement learning defines the objective. Conjecture 1: RL is enough to formalise the problem of intelligence. Deep learning (DL) gives mechanisms for optimising objectives. Conjecture 2: Deep neural networks can represent and learn any computable function. Deep RL combines the RL problem with DL solution. Conjecture 3: RL + DL can solve the problem of intelligence. Silver et al. (2021) present the Reward-is-Enough hypothesis: “Intelligence, and its associated abilities, can be understood as subserving the maximisation of reward by an agent acting in its environment.”

Russell and Norvig’s AI textbook states that “reinforcement learning might be considered to encompass all of AI: an agent is placed in an environment and must learn to behave successfully therein” and “reinforcement learning can be viewed as a microcosm for the entire AI problem” (Russell and Norvig, 2009). It is also shown that tasks with computable descriptions in computer science can be formulated as RL problems (Hutter, 2005).

It is desirable to have RL systems that work in the real world with real benefits. However, there are many theoretical, algorithmic, and practical challenges before RL is widely applied: generalization, sample efficiency, exploration vs. exploitation dilemma, credit assignment, safety, explainability, and technical debts, just name a few.

To share knowledge and lessons, as well as to identify key research challenges, for the topic of RL for real life, we organized workshops in ICML 2019 and ICML 2021, as well as a virtual workshop in 2020. We brought together researchers and practitioners from industry and academia interested in addressing practical and/or theoretical issues that arise when applying RL to real-life scenarios. Researchers presented some of their latest results, shared first-hand lessons and experience from real-life deployments, and identified key research problems and open challenges. We also guest-edited a special issue and an ongoing second special issue for the Machine Learning journal. More information can be found on the website: https://sites.google.com/view/RL4RealLife

This article is a gentle discussion about the field of reinforcement learning for real life, about opportunities and challenges, with perspectives and without technical details, touching a broad range of topics. The article is based on both historical and recent research papers, surveys, tutorials, talks, blogs, and books. Various groups of readers, like researchers, engineers, students, managers, investors, officers, and people wanting to know more about the field, may find
We organize the rest of the article as follows. We first give a brief introduction to RL, and its relationship with deep learning, machine learning and AI. Then we discuss opportunities of RL, in particular, applications in products and services, games, recommender systems, robotics, transportation, economics and finance, healthcare, education, combinatorial optimization, computer systems, and science and engineering. The we discuss challenges, in particular, 1) foundation, 2) representation, 3) reward, 4) model, simulation, planning, and benchmarks, 5) learning to learn a.k.a. meta-learning, 6) off-policy/offline learning, 7) software development and deployment, 8) business perspectives, and 9) more challenges. We conclude with a discussion, attempting to answer: “Why has RL not been widely adopted in practice yet?” and “When is RL helpful?”.

2 A Brief Introduction to RL

Machine learning is about learning from data and making predictions and/or decisions. We usually categorize machine learning into supervised learning, unsupervised learning, and reinforcement learning. Supervised learning works with labeled data, including classification and regression with categorical and numerical outputs, respectively. Unsupervised learning finds patterns from unlabelled data, e.g., clustering, principle component analysis (PCA) and generative adversarial network (GAN). In RL, there are evaluative feedbacks but no supervised labels. Evaluative feedbacks can not indicate whether a decision is correct or not, as labels in supervised learning. Supervised learning is usually one-step, and considers only immediate cost or reward, whereas RL is sequential, and ideal RL agents are far-sighted and consider long-term accumulative rewards. RL has additional challenges like credit assignment and exploration vs. exploitation, comparing with supervised learning. Moreover, in RL, an action can affect next and future states and actions, which results in distribution shift inherently. Deep learning (DL), or deep neural networks (DNNs), can work with/as these and other machine learning approaches. Deep learning is part of machine learning, which is part of AI. Deep RL is an integration of deep learning and RL.

An RL agent interacts with the environment over time to learn a policy, by trial and error, that maximizes the long-term, cumulated reward. At each time step, the agent receives an observation, selects an action to be executed in the environment, following a policy, which is the agent’s behaviour, i.e., a mapping from an observation to actions. The environment responds with a scalar reward and by transitioning to a new state according to the environment dynamics.

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1RL can be viewed as equivalent to AI, as discussed earlier. As a framework for decision making, RL is beyond prediction, which is usually the task by ML, usually referring to supervised learning and unsupervised learning. As a result, the categorization may appear confusing and contradictory. Here we present both perspectives: 1) that DL and RL are part of ML, which is part of AI, and 2) that RL is equivalent to AI.
In an episodic environment, this process continues until the agent reaches a terminal state and then it restarts. Otherwise, the environment is continuing without a terminal state. There is a discount factor to measure the influence of future award. The model refers to the transition probability and the reward function. The RL formulation is very general: state and action spaces can be discrete or continuous; an environment can be a multi-armed bandit, an MDP, a partially observable MDP (POMDP), a game, etc.; and an RL problem can be deterministic, stochastic, dynamic, or adversarial.

A state or action value function measures the goodness of each state or state action pair, respectively. It is a prediction of the return, or the expected, accumulative, discounted, future reward. The action value function is usually called the $Q$ function. An optimal value is the best value achievable by any policy, and the corresponding policy is an optimal policy. An optimal value function encodes global optimal information, i.e., it is not hard to find an optimal policy based on an optimal state value function, and it is straightforward to
find an optimal policy with an optimal action value function. The agent aims to maximize the expectation of a long-term return or to find an optimal policy.

When the system model is available, we may use dynamic programming methods: policy evaluation to calculate value/action value function for a policy, and value iteration or policy iteration for finding an optimal policy, where policy iteration consists of policy evaluation and policy improvement. Monte Carlo (MC) methods learn from complete episodes of experience, not assuming knowledge of transition nor reward models, and use sample means for estimation. Monte Carlo methods are applicable only to episodic tasks. In model-free methods, the agent learns with trial and error from experience directly; the model, usually the state transition, is not known. RL methods that use models are model-based methods; the model may be given or learned from experience.

The prediction problem, or policy evaluation, is to compute the state or action value function for a policy. The control problem is to find the optimal policy. Planning constructs a value function or a policy with a model.

In an online mode, algorithms are trained on data acquired in sequence. In an offline mode, or a batch mode, algorithms are trained on a collection of data.

Temporal difference (TD) learning learns state value function directly from experience, with bootstrapping from its own estimation, in a model-free, online, and fully incremental way. With bootstrapping, an estimate of state or action value is updated from subsequent estimates. TD learning is an on-policy method, with samples from the same target policy. Q-learning is a temporal difference control method, learning an optimal action value function to find an optimal policy. Q-learning is an off-policy method, learning with experience trajectories from some behaviour policy, but not necessarily from the target policy. The notion of on-policy and off-policy can be understood as “same-policy” and “different-policy”, respectively.

In tabular cases, a value function and a policy are stored in tabular forms. Function approximation is a way for generalization when the state and/or action spaces are large or continuous. Function approximation aims to generalize from examples of a function to construct an approximate of the entire function. Linear function approximation is a popular choice, partially due to its desirable theoretical properties. A function is approximated by a linear combination of basis functions, which usually need to be designed manually. The coefficients, or weights, in the linear combination, need to be found by learning algorithms.

We may also have non-linear function approximation, in particular, with DNNs, to represent the state or observation and/or actions, to approximate value function, policy, and model (state transition function and reward function), etc. Here, the weights in DNNs need to be found. We obtain deep RL methods when we integrate deep learning with RL. Deep RL is popular and has achieved stunning achievements recently.

TD learning and Q-learning are value-based methods. In contrast, policy-based methods optimize the policy directly, e.g., policy gradient. Actor-critic algorithms update both the value function and the policy.

There are several popular deep RL algorithms. DQN integrates Q-learning with DNNs, and utilizes the experience replay and a target network to sta-
bilize the learning. In experience replay, experience or observation sequences, i.e., sequences of state, action, reward, and next state, are stored in the replay buffer, and sampled randomly for training. A target network keeps its separate network parameters, which are for the training, and updates them only periodically, rather than for every training iteration. Mnih et al. (2016) present Asynchronous Advantage Actor-Critic (A3C), in which parallel actors employ different exploration policies to stabilize training, and the experience replay is not utilized. Deterministic policy gradient can help estimate policy gradients more efficiently. Silver et al. (2014) present Deterministic Policy Gradient (DPG) and Lillicrap et al. (2016) extend it to Deep DPG (DDPG). Trust region methods are an approach to stabilize policy optimization by constraining gradient updates. Schulman et al. (2015) present Trust Region Policy Optimization (TRPO) and Schulman et al. (2017) present Proximal Policy Optimization (PPO). Haarnoja et al. (2018) present Soft Actor-Critic (SAC), an off-policy algorithm aiming to simultaneously succeed at the task and act as randomly as possible. Fujimoto et al. (2018) present Twin Delayed Deep Deterministic policy gradient algorithm (TD3) to minimize the effects of overestimation on both the actor and the critic. Fujimoto and Gu (2021) present a variant of TD3 for offline RL.

A fundamental dilemma in RL is the exploration vs. exploitation trade-off. The agent needs to exploit the currently best action to maximize rewards greedily, yet it has to explore the environment to find better actions, when the policy is not optimal yet, or the system is non-stationary. A simple exploration approach is $\epsilon$-greedy, in which an agent selects a greedy action with probability $1 - \epsilon$, and a random action otherwise.

## 3 Opportunities

Some years ago we talked about potential applications of machine learning in industry, and ML is already in many large scale production systems. Now we are talking about RL, and RL starts to appear in production systems. Contextual bandits are a “mature” technique that can be widely applied. RL is “mature” for many single-, two-, and multi-player games. We will probably see more results in recommendation/personalization soon. System optimization and operations research are expected to draw more attention. Robotics and healthcare are already at the center of attention. In the following, we discuss several successful applications. Note, topics in subsections may overlap, e.g, robotics may also appear in education and healthcare, computer systems are involved in all topics, combinatorial optimization can be applied widely, like in transportation and computer systems, and science and engineering are general areas. There are vast number of papers about RL applications. See e.g., Li (2019b) and a blog\footnote{https://medium.com/@yuxili/rl-applications-73ef685c07eb} (Both were last updated in 2019.)
3.1 Production and Services

Several RL applications have reached the stage of production and/or services.

The Microsoft Real World Reinforcement Learning Team created Decision Service (Agarwal et al., 2016), and received the 2019 Inaugural ACM SIGAI Industry Award for Excellence in Artificial Intelligence. Furthermore, Microsoft launched Personalizer as part of Azure Cognitive Services within Azure AI platform, with wide applications inside like in more Microsoft products and services, Windows, Edge browser, Xbox, and outside of Microsoft. Microsoft also launched Project Bonsai for building autonomous systems.

Google has applied RL in a diverse application areas, like recommendation (Chen et al., 2019a; Le et al., 2019), chip design (Mirhoseini et al., 2021), and AutoML, which attempts to make ML easily accessible. Google Cloud AutoML provides services like the automation of neural architecture search (Zoph and Le, 2017; Zoph et al., 2018), device placement optimization (Mirhoseini et al., 2017), and data augmentation (Cubuk et al., 2019). Co-Reyes et al. (2021) recently automate RL algorithms themselves.

https://sigai.acm.org/awards/industry_award.html See the open source at https://github.com/Microsoft/mwt-ds and the webpage at https://ds.microsoft.com.
See a blog at https://blogs.microsoft.com/ai/reinforcement-learning/ https://www.microsoft.com/en-us/ai/autonomous-systems-project-bonsai
Facebook has open-sourced ReAgent (Gauci et al., 2019), an RL platform for products and services like notification delivery.

Didi has applied RL to ride sharing order dispatching (Qin et al., 2020), and won the INFORMS 2019 Wagner Prize Winner.

OpenAI recently proposes InstructGPT to fine-tune GPT-3 large language models with human feedback for user intent alignment (Ouyang et al., 2022).

### 3.2 Games

We have witnessed breakthroughs in RL/AI recently, in particular, in games.

Atari games are for single-player games and single-agent decision making in general. Mnih et al. (2015) introduce Deep Q-Network (DQN), which ignited the current round of popularity of deep RL. Recently, Agent57 (Badia et al., 2020) and Go-Explore (Ecoffet et al., 2021) achieve superhuman performance for all 57 Atari games.

Computer Go is a two-player perfect information zero-sum game, a very hard problem, pursued by many researchers for decades. AlphaGo made a phenomenal achievement by defeating a world champion, and set a landmark in AI. Silver et al. (2016) introduce AlphaGo. Silver et al. (2017) introduce AlphaGo Zero, mastering the game of Go without human knowledge. Silver et al. (2018) introduce AlphaZero, extending AlphaGo Zero to more games like chess and shogi (Japanese chess). Tian et al. (2019) reimplement AlphaZero, open source it, and report an analysis. The core techniques are deep learning, reinforcement learning, Monte Carlo tree search (MCTS) (Gelly et al., 2012), upper confidence bound for trees (UCT) (Kocsis and Szepesvári, 2006), self-play and policy iteration. The series of AlphaGo, AlphaGo Zero, and AlphaZero have lifted the bars for Go, chess, and shogi so high that it is hard or impossible for human players to compete with AI programs.

Moreover, (deep) RL has shown its strength in multi-player and/or imperfect information games. Moravčík et al. (2017) introduce DeepStack and Brown and Sandholm (2017) introduce Libratus, for no-limit, heads-up Texas Hold’em Poker. The core techniques are counterfactual regret minimization (Zinkevich et al., 2007) and policy iteration. DeepStack/Libratus are for two-player imperfect information zero-sum games, a family of problems inherently difficult to solve. Brown and Sandholm (2019) is an attempt for multi-player poker. Schmid et al. (2021) propose to combine guided search, self-play, and game-theoretic reasoning for both perfect and imperfect information games.

Deepmind AlphaStar defeats top human players at StarCraft II, a complex Real-Time Strategy (RTS) game (Vinyals et al., 2019). Deepmind has achieved human-level performance in Catch The Flag (Jaderberg et al., 2019). OpenAI Five defeats good human players at Dota 2 (OpenAI et al., 2019). Baker et al. (2020) show emergent strategies with a self-supervised autocurriculum in hide-and-seek. Such achievements in multi-player games show the progress in mastering tactical and strategical team plays.

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See the open source at [https://github.com/facebookresearch/ReAgent](https://github.com/facebookresearch/ReAgent).
Games correspond to fundamental problems in AI, computer science, and many real life scenarios. Each of the above represents a big family of problems and the underlying techniques can be applied to a large number of applications. Single agent decision making is by nature widely applicable. AlphaGo series papers mention the following application areas: general game-playing, classical planning, partially observed planning, scheduling, and constraint satisfaction. DeepStack paper mentions: defending strategic resources and robust decision making for medical treatment recommendations. Libratus paper mentions: business strategy, negotiation, strategic pricing, finance, cybersecurity, military applications, auctions, and pricing.

It is straightforward to think about applying techniques in AlphaGo series to discrete problems. [Bertsekas (2022)] discusses lessons from AlphaZero for continuous problems in optimal, model predictive, and adaptive control, and sheds light on the benefits of on-line decision making on top of off-line training.

The above is about game playing. RL is “mature” for many single-, two- and multi-player games. There are other aspects of games, e.g., game testing [Roohi et al., 2018; Zheng et al., 2019] and procedural content generation [Liu et al., 2021a]. Sports can be regarded as games in real life. [Won et al., 2020] report a curling robot with human-level performance. Liu et al., 2021b) investigate simulated humanoid football from motor control to team cooperation. [Wurman et al., 2022] develop automobile racing agent, winning the world’s best e-sports drivers.

Games to AI is like fruit flies to genetics. Games have the potential to make us better and change the world [McGonigal, 2011; Schell, 2020; Yannakakis and Togelius, 2018].

### 3.3 Recommender System

Recommendation and personalization are powered by machine learning and data mining [Aggarwal, 2016], by bandits [Lattimore and Szepesvári, 2018; Li et al., 2010], and more and more by general RL [Zhao et al., 2021]. [Chen et al., 2019a] propose to scale REINFORCE to a production top-K recommender system for YouTube with a large scale action space, with a top-K off-policy method to tackling the issues of biases due to learning from feedback logs generated from multiple behavior policies and recommendations with multiple items. [Je et al., 2019] propose RecSim, a configurable recommender systems environment.

[Gauci et al., 2019] present ReAgent[7] Facebook’s open source applied RL platform, featuring data preprocessing, feature normalization, data understanding tool, deep RL model implementation, multi-node and multi-GPU training, counterfactual policy evaluation, optimized serving, and tested algorithms, considering real life issues like large datasets with varying feature types and distributions, high dimensional action spaces, slow feedback loop in contrast to simulation, and, more care for experiments in real systems. The authors also

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[7] It is renamed from Horizon. See [https://github.com/facebookresearch/ReAgent](https://github.com/facebookresearch/ReAgent).
discuss cases of real life deployment notifications at Facebook, including push notifications and page administrator notifications.

Theocharous et al. (2020) discuss RL for strategic recommendations. Dacrema et al. (2019) and Rendle et al. (2019) conduct critical analysis of recommender systems.

In some sense, all RL problems are about recommendations: recommend an action/strategy for a given state/observation. That is, recommendation is about decision making. Here we take the narrow view of recommendations as discussed above, in particular, in Web and e-commerce applications.

3.4 Robotics

Robotics is a classical application area for RL (and optimal control) and has wide applications, e.g., in manufacture, supply chain, healthcare, etc. Robotics pose challenges to RL, including 1) dimensionality, 2) real-world examples, 3) under-modeling (models not capturing all details of system dynamics) and model uncertainty, and 4) reward and goal specification (Kober et al., 2013). RL provides tractable approaches to robotics, 1) through representation, including state-action discretization, value function approximation, and pre-structured policies; 2) through prior knowledge, including demonstration, task structuring, and directing exploration; and 3) through models, including mental rehearsal, which deals with simulation bias, real-world stochasticity, and optimization efficiency with simulation samples, and approaches for learned forward models (Kober et al., 2013).

DL and RL have enabled rapid progress in robotics. OpenAI trained Dactyl for a human-like robot hand to dextrously manipulate physical objects (OpenAI et al., 2018). A series of work has advanced the progress in quadrupedal robots locomotion over challenging terrains in the wild, integrating both exteroceptive and proprioceptive perception (Hwangbo et al., 2019; Lee et al., 2020; Miki et al., 2022). Peng et al. (2018) present DeepMimic for simulated humanoid to perform highly dynamic and acrobatic skills. Peng et al. (2021) propose to combine adversarial motion priors with RL for stylized physics-based character animation. Luo et al. (2021) investigate policies for industrial assembly with RL and imitation learning, tackling the prohibitively large design space. Krishnan et al. (2021) introduce a simulator for resource-constrained autonomous aerial robots. Wurman et al. (2022) develop automobile racing agent in simulation, the PlayStation game Gran Turismo, to win the world’s best e-sports drivers.

Barz et al. (2021) review how to train robots with deep RL and discuss outstanding challenges and strategies to mitigate them: 1) reliable and stable learning; 2) sample efficiency: 2.1) off-policy algorithms, 2.2) model-based algorithms, 2.3) input remapping for high-dimensional observations, and 2.4) offline training; 3) use of simulation: 3.1) better simulation, 3.2) domain randomization, and 3.3) domain adaptation; 4) side-stepping exploration challenges: 4.1) initialization, 4.2) data aggregation, 4.3) joint training, 4.4) demonstrations in model-based RL, 4.5) scripted policies, and 4.6) reward shaping; 5) generalization: 5.1) data diversity and 5.2) proper evaluation; 6) avoiding model expoli-
tion; 7) robot operation at scale: 7.1) experiment design, 7.2) facilitating continuous operation, and 7.3) non-stationarity owing to environment changes; 8) asynchronous control: thinking and acting at the same time; 9) setting goals and specifying rewards; 10) multi-task learning and meta-learning; 11) safe learning: 11.1) designing safe action spaces, 11.2) smooth actions, 11.3) recognizing unsafe situations, 11.4) constraining learned policies, and 11.5) robustness to unseen observations; and 12) robot persistence: 12.1) self-persistence and 12.2) task persistence.

Abbeel (2021) discusses that, similar to the pre-training then finetuning in computer vision on ImageNet and in NLP, like GPT-X and BERT, on Internet text, we might be able to pre-train large-scale neural networks for robotics as a general solution, with unsupervised representation learning on Internet video and text, with unsupervised (reward-free) RL pre-training, mostly on simulators and little on the real world data, with human-in-the-loop RL, and with few shot imitation learning on demonstrations.

Mahmood et al. (2018) benchmark RL algorithms on real world robots. Kroemer et al. (2021) review robot learning for manipulation. Brunke et al. (2021) survey safety issues in robotics. Amazon has launched a physical RL testbed AWS DeepRacer, together with Intel RL Coach.

3.5 Transportation

Transportation is a critical infrastructure for everyday life and work, and it is related with supply chain and smart cities. There are recent work in transportation like traffic light control and autonomous driving; see e.g. Haydari and Yilmaz (2022) for a survey. Wu et al. (2021) present Flow, a benchmark for RL in traffic control. Zhou et al. (2020) present a simulation platform for multi-agent RL in autonomous driving.

Here we discuss applying RL to ridesharing (Qin et al., 2020, 2021). Ridesharing order dispatching faces many challenges. The supply and demand are dynamic and stochastic. Short system response time and reliability are expected. There are multiple business objectives. For a driver-centric objective, we want to maximize the total income of the drivers on the platform; whereas for a passenger-centric objective, we want to minimize the average pickup distance of all the assigned orders. Marketplace efficiency metrics concern with response rate and fulfillment rate. Production requirements and constraints consider computational efficiency, system reliability, and changing business requirements. Qin et al. (2020) discuss Didi’s solution approaches to ridesharing order dispatching, from the myopic yet practical combinatorial optimization, to semi-Markov decision process, tabular temporal difference learning, deep (hierarchical) RL, and transfer learning. Qin et al. (2021) discuss RL for operational problems in ridesharing, including: pricing, online matching, vehicle repositioning, route guidance (navigation), ride-pooling (carpool), vehicle routing problem (VRP), model predictive control (MPC), data sets & environments, and discuss challenges and opportunities, including ride-pooling, joint optimization, heterogeneous fleet, simulation & Sim2Real, non-stationarity, and business strategies.
3.6 Economics and Finance

RL is a natural solution to many sequential decision making problems in economics and finance, like policy design, option pricing, trading, and portfolio optimization, etc.

Options are fundamental financial instruments. Longstaff and Schwartz (2001); Tsitsiklis and Van Roy (2001); Li et al. (2009) propose methods to calculate the conditional expected value of continuation, the key to American option pricing. Wang et al. (2019) propose a buying winners and selling losers investment strategy with deep RL, leveraging the momentum phenomenon in finance. Liu et al. (2020) introduce a deep RL library to develop stock trading strategies, and Liu et al. (2021c) build a universe of market environments for data-driven quantitative finance.

Zheng et al. (2021) propose AI Economist to design optimal economic policies with deep RL to address the issues with counterfactual data, behavioral models, and evaluation of policies and behavioral responses.

There are two schools in finance: Efficient Markets Hypothesis (EMH) and behavioral finance (Lo, 2004). According to EMH, “prices fully reflect all available information” and are determined by the market equilibrium. However, psychologists and economists have found a number of behavioral biases that are native in human decision-making under uncertainty. For example, Amos Tversky and Daniel Kahneman demonstrate the phenomenon of loss aversion, in which people tend to strongly prefer avoiding losses to acquiring gains (Kahneman, 2011). Prashanth et al. (2016) investigate prospect theory with RL. Lo (2004) proposes the Adaptive Market Hypothesis to reconcile EMH and behavioral finance, where the markets are in the evolutionary process of competition, mutation, reproduction and natural selection. RL may play an important role in this fundamental market paradigm.

3.7 Healthcare

Personalized medicine systematically optimizes patients’ health care, in particular, for chronic conditions and cancers using individual patient information, potentially from electronic health/medical record (EHR/EMR). Dynamic treatment regimes (DTRs) or adaptive treatment strategies are sequential decision making problems (Chakraborty and Murphy, 2014). Liu et al. (2018b) study off-policy policy evaluation and its application to sepsis treatment. Kallus and Zhou (2018) study confounding-robust policy improvement and its application to acute ischaemic stroke treatment. Tomkins et al. (2021) learn personalized user policies from limited data and non-stationary responses to treatments, achieve a high probability regret bound, perform an empirical evaluation, and conduct a pilot study in a live clinical trial. Gottesman et al. (2020) study interpretable RL by highlighting influential transitions and apply it to medical simulations and intensive care unit (ICU) data. Menictas et al. (2019) dis-

https://github.com/AI4Finance-Foundation
cuss AI decision making in mobile healthcare with micro-randomized trials and just-in-time adaptive interventions (JITAIs).

RL has shown its utility in combating the ongoing pandemic COVID-19. Bastani et al. (2021) propose to use bandits algorithms for COVID-19 tests in Greece. Capobianco et al. (2021) study how to optimize mitigation policies considering both economic impact and hospital capacity. Colas et al. (2021) propose a toolbox for optimizing control policies in epidemiological models. Trott et al. (2021) propose to optimize economic and public policy, in particular, for COVID-19, with AI Economist (Zheng et al., 2021).

Gottesman et al. (2019) present guidelines for reinforcement learning in healthcare. Yu et al. (2023) present a survey about RL in healthcare.

3.8 Education

RL/AI can help education with recommendation, personalization, and adaptation, etc. Cai et al. (2021) propose an educational conversational agent with rules integrated with contextual bandits for math concepts explanation, practice questions, and customized feedbacks. Doroudi et al. (2019) review RL for instructional sequencing, and show that ideas and theories from cognitive psychology and learning sciences help improve performance. Oudeyer et al. (2016) discuss theory and applications of intrinsic motivation, curiosity, and learning in educational technologies.

Singla et al. (2021) present opportunities and challenges for RL for education based on a recent workshop. Singla et al. (2021) identify the following challenges: 1) lack of simulation environments, 2) large or unbounded state space representations, 3) partial observability of students’ knowledge, 4) delayed and noisy outcome measurements, and 5) robustness, interpretability, and fairness. Singla et al. (2021) list the following research directions: 1) personalizing curriculum across tasks, 2) providing hints, scaffolding, and quizzing, 3) adaptive experimentation and A/B testing, 4) human student modelling, and 5) content generation. See https://rl4ed.org/edm2021/ for more details, in particular, invited talks by Emma Brunskill and Shayan Doroudi among others.

3.9 Combinatorial Optimization

Combinatorial optimization is relevant to a large range of problems in operations research, AI and computer science, e.g., travelling salesman problem (TSP) (Vinyals et al., 2015), vehicle routing problem (VRP) (Chen and Tian, 2019; Lu et al., 2020), scheduling (Mao et al., 2019b), network planning (Zhu et al., 2021), and ride-sharing (Qin et al., 2020, 2021) as discussed earlier. Many combinatorial optimization problems are NP-hard, and (traditional) algorithms follow three approaches: exact algorithms, approximate algorithms, and heuristics, and all of which require specialized knowledge and human efforts for trial-and-error. Machine learning can help in several ways (Bengio et al., 2021b). In end-to-end learning, a solution is directly provided to the problem by applying the trained ML model to inputs instance, e.g., in Vinyals et al. (2015). Machine
learning can help to configure algorithms, e.g., for hyper-parameters like learning rate. Machine learning can work alongside with optimization algorithms, e.g., selecting the branching variable in branch and bound methods, like Gasse et al. (2019), and learning heuristics to improve the solution, like Chen and Tian (2019) and Lu et al. (2020).

3.10 Computer Systems

RL has been applied to the whole spectrum of computer systems, from the very bottom hardware, to system softwares, to RL/ML/AI themselves, to networking systems, to various applications, e.g., chip design (Mirhoseini et al., 2021), neural architecture search (Zoph and Le, 2017), compiler (Cummins et al., 2021), cluster scheduling (Mao et al., 2019b), network planning (Zhu et al., 2021), device placement (Mirhoseini et al., 2017), data augmentation (Cubuk et al., 2019), database management system (DBMS) (Zhang et al., 2019), software testing (Zheng et al., 2019), conversational AI (Gao et al., 2019), natural language processing (NLP) (Wang et al., 2018), computer vision (Lu et al., 2019), and automating RL algorithms themselves (Co-Reyes et al., 2021; Guez et al., 2018). Mao et al. (2019a) present Park, an open platform for learning augmented computer systems, covering a wide range of systems problems. See Luong et al. (2019) for a survey about applications of deep RL in communications and networking. Computers are ubiquitous, so in some sense computer systems can cover all topics we discuss in this article.

3.11 Science and Engineering

A problem in natural science and engineering may come with a clear objective function straightforward to evaluate, in particular, when comparing with problems in social sciences. The scientific and engineering understandings can help build effective inductive priors, improve search efficiency, and/or construct models/simulators. Here we list some examples. Todorov et al. (2012) propose the physics engine Mujoco for model-based control. Seth et al. (2018) propose OpenSim for human and animal movement with musculoskeletal dynamics and neuromuscular control. Habitat 2.0 (Szot et al., 2021), Isaac Gym (Makoviy-chuk et al., 2021), and ThreeDWorld (Gan et al., 2021) provide interactive multi-modal physical simulation platforms.

Many problems in science and engineering, including topics we discuss earlier, like robotics and transportation, as well as healthcare, finance, and economics, are traditionally modelled as optimal control or operations research problems, or generally, dynamic programming or (stochastic) optimization problems. See Section 4.1 for more discussion.

Degrave et al. (2022) report an extraordinary attainment applying deep RL to nuclear fusion, promising for sustainable energy. RL has been applied to chemical retrosynthesis (Segler et al., 2018) and drug discovery (Popova et al., 2018; Zhavoronkov et al., 2019). Lazic et al. (2018) from Google AI study data center cooling, a real-world physical system, with model-predictive control
(MPC) and RL. Zhan et al. (2021) propose to optimize combustion for thermal power generating units with offline RL. Henry and Ernst (2021) propose an RL environment Gym-ANM for active network management tasks in electricity distribution systems. Chen et al. (2021b) review RL in power systems. Shin et al. (2019) and Nian et al. (2020) review RL in process control. Kiumarsi et al. (2018) review RL in optimal and autonomous control.

4 Challenges

Although RL has made significant progress, there are still many issues. Sample efficiency, credit assignment, exploration vs. exploitation, and representation are common issues. Value function approaches with function approximation, in particular with DNNs, encounters the deadly triad, i.e., instability and/or divergence caused by the integration of off-policy, function approximation, and bootstrapping. Reproducibility is an issue for deep RL, i.e., experimental results are influenced by hyperparameters, including network architecture and reward scale, random seeds and trials, environments, and codebases (Henderson et al., 2018). Reward specification may cause problems, and a reward function may not represent the intention of the designer. Figure 3 illustrates challenges of reinforcement learning.

Dulac-Arnold et al. (2021) identify nine challenges for RL to be deployed in real-life scenarios, namely, learning on the real system from limited samples, system delays, high-dimensional state and action spaces, satisfying environmental constraints, partial observability and non-stationarity, multi-objective or poorly specified reward functions, real-time inference, offline RL training from fixed logs, and explainable and interpretable policies. Practitioners report lessons in RL deployment, e.g., Rome et al. (2021), Karampatziakis et al. (2019).

Bearing in mind that there are many issues, there are efforts to address all of them, and RL is an effective technique for many applications. As discussed by Dimitri Bertsekas, a prominent researcher working on RL, on one hand, there are no methods that are guaranteed to work for all or even most problems; on the other hand, there are enough methods to try with a reasonable chance of success for most types of optimization problems: deterministic, stochastic, or dynamic ones, discrete or continuous ones, games, etc. He is cautiously positive about RL applications: “We can begin to address practical problems of unimaginable difficulty!” and “There is an exciting journey ahead!” (Bertsekas, 2019b)

4.1 Foundation

It is critical to have a sound foundation. Theory can usually guide practice. Once the foundation is right, RL will be everywhere.

What is Reinforcement Learning?

It is essential to discuss what is RL, before discussing what is the foundation for RL. RL is rooted in optimal control (in particular, dynamic programming and
Figure 3: Challenges of reinforcement learning. From the bottom to the top, roughly: the foundational disciplines for RL, essential RL elements, core solution methods for RL problems with typical algorithms, theoretical and algorithmic issues and advanced mechanisms for RL solutions, software and business issues, and various applications for RL. (We look forward to more research and practice to enrich the part for software and business issues.)

Markov decision process), learning by trial and error, and temporal difference learning, the latter two being related to animal learning. RL has foundation in theoretical computer science/machine learning, classical AI, optimization, statistics, optimal control, operations research, neuroscience, and psychology. (At the same time, RL also influences these disciplines.) RL has both art and science components. Rather than making it pure science, we need to accept that part of it is art.

The following are literal quotes from Section 1.6 in Sutton and Barto [2018]. “Reinforcement learning is a computational approach to understanding and automating goal-directed learning and decision making. It is distinguished from other computational approaches by its emphasis on learning by an agent from direct interaction with its environment, without requiring exemplary supervision
or complete models of the environment. In our opinion, reinforcement learning is the first field to seriously address the computational issues that arise when learning from interaction with an environment in order to achieve long-term goals.” “Reinforcement learning uses the formal framework of Markov decision processes to define the interaction between a learning agent and its environment in terms of states, actions, and rewards. This framework is intended to be a simple way of representing essential features of the artificial intelligence problem. These features include a sense of cause and effect, a sense of uncertainty and nondeterminism, and the existence of explicit goals.”

Richard Sutton discusses briefly about David Marr’s three levels at which any information processing machine must be understood: computational theory, representation and algorithm, and hardware implementation. AI has surprisingly little computational theory. The big ideas are mostly at the middle level of representation and algorithm. RL is the first computational theory of intelligence. RL is explicitly about the goal, the whats and whys of intelligence.

RL is a set of sequential decision problems. It is not a specific set of algorithmic solutions, like TD, DQN, PPO, evolutionary search, random search, semi-supervised learning, etc. RL has three basic problems and many variations: online RL, offline / batch RL, and planning/simulation optimization. See Szepesvári (2020c).

How to Achieve Stronger Intelligence?

Sutton (2019) argues that “The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin.” This is supported by recent achievements in chess, computer Go, speech recognition, and computer vision. We thus should leverage the great power of general purpose methods: search and learning. Since the actual contents of minds are very complex, we should build in only the meta-methods that can find and capture the arbitrary complexity, and let our methods search for good approximations, but not by us.

Brooks (2019) argues that we have to take into account the total cost of any solution, and that so far they have all required substantial amounts of human ingenuity. As an example, Convolutional Neural Networks (CNNs) were designed by humans to manage translational invariance. However, CNNs still suffer from issues like color constancy, by mistakenly recognizing a traffic stop sign with some pieces of tape on it as a 45 mph speed limit sign. Network architecture design and special purpose computer architecture need human analysis. The current AI still need massive data sets, huge amount of computation, and huge power consumption. Furthermore, Moore’s Law slows down and Dennard scaling breaks down.

Kaelbling (2019) argues that it is constructive to specify the objective, which may be building a practical system in short or long term, understanding intelligence at the level of neural computation or behavior and cognition, or develop

https://www.youtube.com/watch?v=hcJNFdZit-Q
oping mathematical and computational theories. The author’s goal is to design software for intelligent robots. It is somewhat a software engineering problem: given a spec, design the software. However, the more abstract the spec, the more difficult the engineering problem. To craft special-purpose programs with a general-purpose engineering methodology, machine learning is critical to build robots in the factory and to learn to adapt in the wild. When data and computation are not free, relatively general biases like structures, algorithms and reflexes help achieve sample efficient learning.

Szepesvári (2020c) argues that more data and less structure wins is a fallacy. It is from the history of AI, which, however, is still too short. The actual bitter lesson is: We can’t predict what works, what won’t work. We won’t run exhaustive search. A resolution is to diversify: more data, less structure, smarter algorithms, etc. Structure is always present, e.g., in gradient descent and neural architecture. It is important to study structure.

Kaelbling (2020) argues that the foundation for (robot) learning entails sample efficiency, generalization, composition, and incremental learning, which can be achieved by providing proper inductive biases, and meta-learning is an approach.

Botvinick et al. (2019) argue that sample inefficiency comes from two sources: incremental parameter adjustment to maximize generalization and avoid overwriting the effects of earlier learning, and weak inductive bias. The authors propose to address such slowness with episodic memory, meta-learning and their integration, and make the connection to fast and slow learning, which is an idea in psychology underlying a Nobel prize in economics (Kahneman 2011) [Bengio 2020].

Lake et al. (2017) discuss that the following are key ingredients to achieve human-like learning and thinking: 1) developmental start-up software, or cognitive capabilities in early development, including: 1.1) intuitive physics and 1.2) intuitive psychology; 2) learning as rapid model building, including: 2.1) compositionality, 2.2) causality, and 2.3) learning to learn; 3) thinking fast, including: 3.1) approximate inference in structured models and 3.2) model-based and model-free RL.

**RL vs. Optimal Control and Operations Research**

Traditionally optimal control (OC) and operations research (OR) require a perfect model for the problem formulation. RL can work in a model-free mode, and can handle very complex problems via simulation, which may be intractable for model-based OC or OR approaches. AlphaGo, together with many games, are huge problems. RL with a perfect model can return a perfect solution, in the limit. RL with a decent simulator or with decently sufficient amount of data can provide a decent solution. Admittedly, there are adaptive and/or approximate approaches in OC and OR working with imperfect models, and/or for large-scale problems. We see that RL, optimal control, and operations research are merging and advancing together, which is beneficial and fruitful for all these scientific communities.
Sutton and Barto (2018) discuss the relationship between RL and optimal control in Section 1.7, where we quote the following verbatim. “We consider all of the work in optimal control also to be, in a sense, work in reinforcement learning. We define a reinforcement learning method as any effective way of solving reinforcement learning problems, and it is now clear that these problems are closely related to optimal control problems, particularly stochastic optimal control problems such as those formulated as MDPs. Accordingly, we must consider the solution methods of optimal control, such as dynamic programming, also to be reinforcement learning methods. Because almost all of the conventional methods require complete knowledge of the system to be controlled, it feels a little unnatural to say that they are part of reinforcement learning. On the other hand, many dynamic programming algorithms are incremental and iterative. Like learning methods, they gradually reach the correct answer through successive approximations. As we show in the rest of this book, these similarities are far more than superficial. The theories and solution methods for the cases of complete and incomplete knowledge are so closely related that we feel they must be considered together as part of the same subject matter.”

Bertsekas (2019a,b) presents ten key ideas for RL and optimal control: 1) principle of optimality, 2) approximation in value space, 3) approximation in policy space, 4) model-free methods and simulation, 5) policy improvement, rollout, and self-learning 6) approximate policy improvement, adaptive simulation, and Q-learning, 7) features, approximation architectures, and deep neural nets, 8) incremental and stochastic gradient optimization, 9) direct policy optimization: a more general approach, and 10) gradient and random search methods for direct policy optimization.

Powell (2019) regards RL as sequential decision problems, and identifies four types of policies: 1) policy function approximations, e.g., parameterized policies, 2) cost function approximations, e.g., upper confidence bounding (UCB), 3) value function approximations, e.g., Q-learning, and 4) direct lookahead, e.g., Monte Carlo tree search (MCTS), claiming they are universal, i.e., “any policy proposed for any sequential decision problem will consist of one of these four classes, and possibly a hybrid”. Powell (2019) proposes a unified framework based on stochastic control.

Szepesvári (2020c) discusses that RL is not the answer to everything and RL is not the set of popular methods like TD, DQN and PPO. It is normal for certain methods like model predictive control (MPC) and random search to perform well on certain tasks. Methods have strengths and weaknesses. For a certain task, besides RL, we should consider other methods.

Bertsekas (2022) discusses lessons from AlphaZero for continuous problems in optimal, model predictive, and adaptive control. Levine (2018) regards RL and control as probabilistic inference. Recht (2019) surveys RL from the perspective of optimization and control.

There are several recent books at the intersection of RL and optimal control and/or operations research, e.g. Bertsekas (2019a); Powell (2021); Meyn (2022).
More Food for Thoughts

We list some relevant materials below:

- Szepesvári (2020c) presents myths and misconceptions in RL.
- Agarwal et al. (2020a) present the FOCS 2020 Tutorial on the Theoretical Foundations of Reinforcement Learning.
- Krishnamurthy and Sun (2021) present the COLT 2021 Tutorial on Statistical Foundations of Reinforcement Learning.
- Schuurmans (2019), Li (2019a) and Nachum and Dai (2020) discuss optimization in RL.
- Foster et al. (2021) analyze statistical complexity of interactive decision making.
- Theory of Reinforcement Learning Boot Camp at Simons Institute at https://simons.berkeley.edu/workshops/rl-2020-bc.
- Mitchell (2021) discusses why AI is harder than we think.
- Fortnow (2022) discusses fifty years of P vs. NP and the possibility of the impossible with the progress in AI.

4.2 Representation

The “representation” in “representation learning” basically refers to the “feature” in “feature engineering” (Bengio et al., 2013). Representation learning is an approach to automatically finding good features. It plays an indispensable role in the success and further progress in deep learning (LeCun et al., 2015; Bengio et al., 2021a).

Here we discuss “representation” in a broader perspective, i.e., it is relevant not only to function approximation for state/observation, action, value function, reward function, transition probability, but also to agent, environment, and any element in an RL problem. Besides the “feature” for function approximation, we also refer “representation” to problem representation, like MDP, POMDP, and contextual decision process (CDP) (Jiang et al., 2017), and, moreover, for representing knowledge, reasoning, and human intelligence. We attempt to use such a notion of “representation” to unify the roles of (deep) learning in various aspects of (deep) RL.

When the problem is small, a tabular representation suffices to accommodate both states and actions. For large-scale problems, we need function approximation to avoid the curse of dimensionality. One approach is linear function approximation, using basis functions such as polynomial bases, tile-coding, radial basis functions, and Fourier basis (Sutton and Barto, 2018). Recently, nonlinear function approximations, in particular, DNNs, show exciting achievements. Common neural network structures and models include MLP, CNNs, RNNs,
in particular LSTM and GRU, generative adversarial networks (GANs), and (variational) auto-encoder, etc. There are new neural network architectures customized for RL problems, e.g., value iteration networks (VIN) (Tamar et al., 2016), value prediction network (VPN) (Oh et al., 2017), and MCTSnets (Guez et al., 2018).

General Value Functions (GVFs) learn, represent, and use knowledge of the world (Sutton et al., 2011). Successor representation is an approach for state distributions, which is related to value function. Hierarchical representations, such as options (Sutton et al., 1999), handle temporal abstraction. Multi-agent RL model interactions among agents (Hernandez-Leal et al., 2019; Zhang et al., 2021a). Relational RL (Zambaldi et al., 2019) integrates statistical relational learning and reasoning with RL to handle entities and relations.

Unsupervised learning takes advantage of the massive amount of data without labels. Self-supervised learning is a special type of unsupervised learning, in which labels are created from data, although not given. Unsupervised auxiliary learning (Jaderberg et al., 2017; Mirowski et al., 2017), Horde (Sutton et al., 2011), and contrastive unsupervised representations for RL (Srinivas et al., 2020) are example approaches taking advantages of non-reward training signals in environments. Srinivas and Abbeel (2021) present a tutorial on self(un)-supervised representation learning to improve RL, in particular, with contrastive learning (Chen et al., 2020; Hénaff et al., 2020).

There are renewed interests in deploying or designing networks for reasoning. Battaglia et al. (2018) propose “graph networks” as a building block for relational inductive biases, to learning entities, relations, and how to compose them for relational reasoning and combinatorial generalization. There are discussions about addressing issues of current machine learning with causality (Pearl and Mackenzie, 2018), and incorporating more human intelligence into artificial intelligence (Lake et al., 2017). Schölkopf et al. (2021) propose causal representation learning for out-of-distribution generalization.

Although there have been enormous efforts for representation, since RL is fundamentally different from supervised learning and unsupervised learning, an optimal representation for RL is probably different from generic CNNs and RNNs, thus it is desirable to search for an optimal representation for RL. A hypothesis is that this would follow a holistic approach, by considering perception and control together, e.g., in interactive perception (Bohg et al., 2017), rather than treating them separately, e.g., by deciding a CNN to handle visual inputs, then fixing the network and designing a learning procedure to find optimal weights for value function and/or policy. For example, Srinivas et al. (2018) propose plannable representation for goal-directed tasks with gradient-based planning. Srinivas and Abbeel (2021) discuss unsupervised learning for RL. Abbeel (2021) discusses a general solution, in particular, pre-training, for robotics. However, note that Schuurmans (2020) discusses reductionism in RL.
4.3 Reward

Rewards provide evaluative feedbacks for RL agents to make decisions. Silver et al. (2021) present the Reward-is-Enough hypothesis.

Rewards may be so sparse that it is challenging for learning algorithms, e.g., in computer Go, a reward occurs at the end of a game. Hindsight Experience Replay (HER) (Andrychowicz et al., 2017) is a way to handle sparse rewards. Unsupervised auxiliary learning (Jaderberg et al., 2017) is an unsupervised way harnessing environmental signals. Intrinsic motivation (Barto, 2013; Singh et al., 2010) is a way to provide intrinsic rewards. Colas et al. (2020) present a short survey for intrinsically motivated goal-conditioned RL. Srinivas and Abbeel (2021) present a tutorial on reward-free RL.

Reward shaping is to modify reward function to facilitate learning while maintaining optimal policy (Ng et al., 2000). It is usually a manual endeavour. Jaderberg et al. (2018) employ a learning approach in an end-to-end training pipeline.

Reward functions may not be available for some RL problems. In imitation learning (Osa et al., 2018), an agent learns to perform a task from expert demonstrations, with sample trajectories from the expert, without reinforcement signals. Two main approaches for imitation learning are behavioral cloning and inverse RL. Behavioral cloning, or learning from demonstration, maps state-action pairs from expert trajectories to a policy, maybe as supervised learning, without learning the reward function (Levine, 2020). Inverse RL is the problem of determining a reward function given observations of optimal behavior (Ng and Russell, 2000). Probabilistic approaches are developed for inverse RL with maximum entropy (Ziebart et al., 2008) to deal with uncertainty in noisy and imperfect demonstrations. Ross et al. (2010) reduce imitation learning and structured prediction to no-regret online learning, and propose DAGGER, which requires interaction with the expert.

A reward function may not represent the intention of the designer. A negative side effect of a misspecified reward refers to potential poor behaviors resulting from missing important aspects. An old example is about the wish of King Midas, that everything he touched, turned into gold. Unfortunately, his intention did not include food, family members, and many more. Hadfield-Menell et al. (2016) propose a cooperative inverse RL (CIRL) game for the value alignment problem. Dragan (2020) talks about optimizing intended reward functions.

Christiano et al. (2017) propose the approach of RL from human feedback, i.e., by defining a reward function with preferences between pairs of trajectory segments, to tackle with the problems without well-defined goals and without experts’ demonstrations. This helps to improve the alignment between humans’ values and the objectives of RL systems. Lee et al. (2021) present unsupervised pre-training and preference-based learning via relabeling experience, to improve the efficiency of human-in-the-loop feedbacks with binary labels, i.e. preferences, provided by a supervisor. Ouyang et al. (2022) propose to fine-tune large language models GPT-3 with human feedback, in particular, with RL (Christiano et al., 2017), to follow instructions for better alignment with humans’
values. Wirth et al. (2017) present a survey of preference-based RL methods. Zhang et al. (2021c) survey human guidance for sequential decision-making.

From self-motivation theory (Ryan and Deci 2020), the basic psychological needs of autonomy, competence and relatedness mediate positive user experience outcomes such as engagement, motivation and thriving (Peters et al. 2018). Flow is about the psychology of optimal experience (Csikszentmihalyi 2008). As such, they constitute specific measurable parameters for which designers can design in order to foster these outcomes within different spheres of experience. Such self-motivation theory and flow, or positive psychology, may help the design of reward and human-computer interaction (HCI), and there are applications in games (Tyack and Mekler 2020), education (Ryan and Deci 2020), etc. Cruz and Igarashi (2020) survey design principles for interactive RL. It appears that self-motivation theory is under-explored in RL/AI.

4.4 Model, Simulation, Planning, and Benchmarks

An RL model refers to the transition probability and the reward function, mapping states and actions to distributions over next states and expected rewards, respectively. A model or a simulator specifies how an agent interacts with an environment. A dataset may be collected offline, or generated by the dynamics rules, a model, or a simulator. A model may be built from a dataset by estimating parameters, and/or with prior (physics) knowledge, or by a generative approach like GANs. A simulator may be built based on a model, explicitly, e.g., from game rules like the Arcade Learning Environment for Atari games (Bellemare et al. 2013; Machado et al. 2018) or computer Go, chess and Shogi (Silver et al. 2018), and physics like Mujoco (Todorov et al. 2012), or implicitly, e.g., those with generative models (Ho and Ermon 2016; Chen et al. 2019b; Shi et al. 2019). A benchmark includes datasets and/or simulators, together with algorithm implementations and evaluation methods. Performance evaluation is essential for learning, engineering, and science; see e.g., Agarwal et al. (2021). Planning works with a model, and may take a form of single agent search like A*, alpha-beta tree search, MCTS, or dynamic programming like value iteration.

Dyna is an early work that learns from both online and simulated data. Value prediction network (VPN) (Oh et al. 2017), SimPLe (Kaiser et al. 2020), and Dreamer (Hafner et al. 2020) are some recent work in model-based RL. Schrittwieser et al. (2020) study how to do planning in Atari games, Go, chess, shoji with a learned model following AlphaZero. Szepesvári (2020) discusses model misspecification of RL. Mordatch and Hamrick (2020) present the ICML 2020 tutorial on model-based methods in RL.

It is easier to train an RL agent in simulation than in reality. Simulation to reality (sim-to-real or sim2real) gaps receive much attention recently, in particular, in robotics. Most RL algorithms are sample intensive and exploration may cause risky policies to the robot and/or the environment. However, a simulator usually can not precisely reflect the reality. How to bridge the sim-to-real gap is critical and challenging. Sim-to-real is a special type of transfer learning.
Open sources play a critical role in the success of this wave of AI, in particular, RL. We list names of some RL benchmarks below, which can be easily found on the Internet: AI Habitat, Amazon AWS DeepRacer, Deepmind, Behaviour Suite, DeepMind Control Suite, DeepMind Lab, DeepMind Memory Task Suite, DeepMind OpenSpiel, DeepMind Psychlab, Deepmind Real-World Reinforcement Learning, DeepMind RL Unplugged, DeepMind TRFL, Facebook ELF, Google Balloon Learning Environment, Google Dopamine, Google Research Football, Intel RL Coach, Meta-World, Microsoft TextWorld, MineRL, Multiagent emergence environments, OpenAI Gym, OpenAI Gym Retro, Procgen Benchmark, PyBullet Gymperium, Ray/RLlib, RLCard, RLPy, Screeps, Serpent.AI, Stanford BEHAVIOR, StarCraft II Learning Environment, The Unity Machine Learning Agents Toolkit (ML-Agents), WordCraft.

In particular, Habitat 2.0 (Szot et al., 2021), Isaac Gym (Makoviychuk et al., 2021), and ThreeDWorld (Gan et al., 2021) provide interactive multi-modal physical simulation platforms. Srivastava et al. (2021) present a benchmark for embodied AI with 100 realistic, diverse and complex household activities in simulation, with the definition, instantiation in a simulator, and evaluation for each activity. Ebert et al. (2021) propose to boost generalization of robotic skills with cross-task and cross-domain datasets and evaluate the hypothesis using a bridge dataset with 7,200 demonstrations for 71 tasks in 10 environments.

There are some RL competitions, usually with datasets. One question remains: Can we have a dataset for RL like the ImageNet for DL? It is a common wisdom among enterprises and high managements to have big datasets ready to take advantage of the achievements of AI and big data. It is probably wiser to prepare datasets for reinforcement learning, in particular, for contextual bandits, to avoid losing battles during the highly likely revolutions empowered by RL, the new type of AI. Different from supervised learning with labelled data, datasets for RL need states/observations, actions and rewards. Moreover, rewards may arrive later, which causes practical issues (Agarwal et al., 2016). The software design needs to consider such issues when preparing datasets for RL. There are RL competitions in conference like NeurIPS. NeurIPS 2021 has a new track on Datasets and Benchmarks.

Digital twin is related to simulator, both of which play an essential role in the emerging metaverse in particular, for the metaverse focusing on science and engineering. Metaverse would be the integration of various techniques, including AI, virtual reality (VR), augmented reality (AR), Internet of Things (IoT), cloud computing, communication (e.g., 5G), block chain, etc. Isaac Gym (Makoviychuk et al., 2021) is part of Nvidia Omniverse. Habitat 2.0 (Szot et al., 2021), ThreeDWorld (Gan et al., 2021), and BEHAVIOR (Srivastava et al., 2021) can be seen as academic efforts in this directions.

Lavin et al. (2021) present nine motifs of simulation intelligence: 1) multi-

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10See https://neptune.ai/blog/best-benchmarks-for-reinforcement-learning for a brief discussion for some of the benchmarks.
11See e.g., https://github.com/seungjaeryanlee/awesome-rl-competitions
12https://en.wikipedia.org/wiki/Metaverse
13See e.g., https://blogs.nvidia.com/blog/2021/12/14/what-is-a-digital-twin/
physics and multi-scale modeling, 2) surrogate modeling and emulation, 3) simulation-based inference, 4) causal modeling and inference, 5) agent-based modeling, 6) probabilistic programming, 7) differentiable programming, 8) open-ended optimization, and 9) machine programming.

4.5 Learning to Learn a.k.a. Meta-learning

Learning to learn, a.k.a. meta-learning, is learning about some aspects of learning. It includes concepts as broad as transfer learning, multi-task learning, one/few/zero-shot learning, learning to reinforcement learn, learning to optimize, learning combinatorial optimization, hyper-parameter learning, neural architecture design, automated machine learning (AutoML)/AutoRL/AutoAI, etc. It is closely related to continual learning and life-long learning. Learning to learn is a core ingredient to achieve strong AI \footnote{Botvinick et al. 2019; Kaelbling 2020; Lake et al. 2017; Sutton 2019}, as discussed in Section 4.1, and has a long history, e.g., Schmidhuber (1987), Bengio et al. (1991), and Thrun and Pratt (1998).

Li and Malik (2017), along with a blog,\footnote{http://bair.berkeley.edu/blog/2017/09/12/learning-to-optimize-with-rl/} divide various learning to learn methods into three categories: learning what to learn; learning which model to learn; and learning how to learn. The authors mention that, roughly speaking, learning to learn “simply means learning something about learning”. The authors discuss that the term of learning to learn has the root in the idea of metacognition by Aristotle in 350 BC,\footnote{http://classics.mit.edu/Aristotle/soul.html} which describes “the phenomenon that humans not only reason, but also reason about their own process of reasoning”. In the category of learning what to learn, the aim is to learn values for base-model parameters, gaining the meta-knowledge of commonalities across the family of related tasks, and to make the base-learner useful for those tasks \footnote{https://github.com/cbfinn/maml}. Examples in this category include methods for transfer learning, multi-task learning, and few-shot learning. In the category of learning which model to learn, the aim is to learn which base-model is most suitable for a task, gaining the meta-knowledge of correlations of performance between various base-models, by investigating their expressiveness and searchability. This learns the outcome of learning. In the category of learning how to learn, the aim is to learn the process of learning, gaining the meta-knowledge of commonalities in learning algorithms behaviors. There are three components for learning how to learn: the base-model, the base-algorithm to train the base-model, and the meta-algorithm to learn the base-algorithm. The goal of learning how to learn is to design the meta-algorithm to learn the base-algorithm, which trains the base-model. Bengio et al. (1991) and Li and Malik (2017) fall into this category. Li and Malik (2017) propose automating unconstrained continuous optimization algorithms with RL.

Finn et al. (2017), along with a blog\footnote{https://github.com/cbfinn/maml} summarize that there are three categories of methods for learning to learn, namely, recurrent models, metric
learning, and learning optimizers. In the approach of recurrent models, a recurrent model, e.g., an LSTM, is trained to take in data points, e.g., (image, label) pairs for an image classification task, sequentially from the dataset, and then processes new data inputs from the task. The meta-learner usually uses gradient descent to train the learner, and the learner uses the recurrent network to process new data. In the approach of metric learning, a metric space is learned to make learning efficient, mostly for few-shot classification. In the approach of learning optimizers, an optimizer is learned, using a meta-learner network to learn to update the learner network to make the learner learn a task effectively. Motivated by the success of using transfer learning for initializing computer vision network weights with the pre-trained ImageNet weights, Finn et al. (2017) propose model-agnostic meta-learning (MAML) to optimize an initial representation for a learning algorithm, so that the parameters can be fine-tuned effectively from a few examples. MAML works for both supervised learning and RL.

Duan (2017) gives a brief review of meta-learning. The author discusses meta-learning for supervised learning, including metric-based models, optimization-based models, and fully generic models, and other applications. The author also discusses meta-learning for control, and proposes to learn RL algorithms and one-shot imitation learning.

The aim of few-shot meta-learning is to train a model adaptive to a new task quickly, using only a few data samples and training iterations (Finn et al., 2017). Transfer learning is about transferring knowledge learned from different domains, possibly with different feature spaces and/or different data distributions (Taylor and Stone, 2009; Pan and Yang, 2010). Curriculum learning (Bengio et al., 2009; Narvekar et al., 2020; Baker et al., 2020; Vinyals et al., 2019), model distillation/compression (Hinton et al., 2014; Czarnecki et al., 2019), and sim-to-real are particular types of transfer learning. Multitask learning (Caruana, 1997) learns related tasks with a shared representation in parallel, leveraging information in related tasks as an inductive bias, to improve generalization, and to help improve learning for all tasks. Schölkopf et al. (2021) discuss causal representation learning for transfer learning, multitask learning, continual learning, RL, etc. See Hutter et al. (2019) for a book on AutoML, Hospedales et al. (2021) for a survey on meta-learning, Singh (2017) for a tutorial about continual learning, Chen et al. (2021a) for a survey and a benchmark on learn to optimize, and Portelas et al. (2020) for a survey on automatic curriculum learning for deep RL.

### 4.6 Off-policy/Offline Learning

Learning from previously collected data is a feasible approach for some problems, esp. when there is no perfect model or high-fidelity simulator. This works to some extent even for challenging problems like AlphaGo (Silver et al., 2016). As the first work in the AlphaGo series, AlphaGo (Silver et al., 2016) initializes the policy with human demonstration data. However, AlphaGo Zero (Silver et al., 2017) and AlphaZero (Silver et al., 2018) learn from scratch, without human knowledge.
and InstructGPT (Ouyang et al., 2022). Moreover, it may be costly, risky, and/or unethical to run a policy in the physical environments, e.g., for healthcare, autonomous driving, and nuclear fusion. Thus off-policy/offline learning attract significant attention recently.

There are two dimensions here: online/offline and on-policy/off-policy learning. In online learning, algorithms are trained on data acquired in sequence. In offline learning, or a batch mode, algorithms are trained on a (fixed) collection of data. In on-policy learning, samples are from the same target policy. In off-policy learning, experience trajectories are usually from some different behaviour policy/policies, but not necessarily from the same target policy. For example, both Q-learning and DQN are off-policy learning algorithms. However, Q-learning is online, while DQN follows a mixture of online mode, by collecting samples on the go, and offline mode, by storing the experience data into a replay buffer and then sampling from it. In recent academic settings, offline learning deals with a fixed dataset. In practice, we expect an iterative and adaptive way, at the basis of minutes, hours, or days, etc., depending on the application. [Levine et al., 2020] and [Kumar and Levine, 2020] present a survey and a tutorial on offline RL, respectively.

In off-policy learning, importance sampling is a standard way to correct the distribution mismatch between the experience data observed from the behaviour policy and those unobserved from the target policy. [Li et al., 2011] study the inverse propensity scoring (IPS) with importance sampling in the setting of contextual bandits and apply it to news article recommendation. A critical issue for importance sampling is the high variance, esp. for the full RL case (Precup et al., 2000). The doubly robust technique was studied e.g. by [Dudik et al., 2011] for contextual bandits, and by [Jiang and Li, 2016] and [Thomas and Brunskill, 2016] for RL, to reduce variance in off-policy learning. [Liu et al., 2018a] propose to calculate importance weights on states, rather than on trajectories, to avoid the “curse of horizon”, i.e., the dependence on the trajectory length. [Nachum et al., 2019] study how to estimate discounted stationary distribution ratios, i.e., the likelihood that a certain state action pair appears in the target policy normalized by the likelihood it appears in the dataset. [Nachum and Dai, 2020] survey duality for RL, including off-policy learning.

There are early examples of offline or batch RL, e.g. least-squares temporal difference (LSTD) (Bradtke and Barto, 1996), least-squares policy iteration (LSPI) (Lagoudakis and Parr, 2003), and fitted Q iteration (Ernst et al., 2005). These approximate dynamic programming approaches suffer the issue of action distribution shift, and modern offline RL attempts to address it, with policy constraints (Kumar et al., 2019), model-based (Yu et al., 2020; Kidambi et al., 2020), value function regularization (Kumar et al., 2020), and uncertainty-based methods (Agarwal et al., 2020b). Constraints may be put on distribution, support, and state-action marginal distributions. Policy constraint methods need to estimate the behavior policy, and tend to be too conservative (Levine et al., 2020; Kumar and Levine, 2020). Model-based offline RL is an alternative approach to avoid unseen outcomes. See [Levine et al., 2020]: [Kumar and Levine, 2020] and the reference for more details. [Fujimoto and Gu, 2021] propose
to add a behavior cloning term to the policy update of TD3 to regularize the policy, aiming to change an online deep RL algorithm minimally to work offline. Fu et al. (2020) present D4RL, datasets and benchmarks for deep data-driven RL. Gülçehre et al. (2020) present RL Unplugged to evaluate and compare offline RL methods.

Off-policy learning answers what-if questions by counterfactual analysis, relating to causal inference closely. Bareinboim (2020) presents a tutorial on causal RL. Pearl and Mackenzie (2018) introduce cause and effect, or causality. The extent of intelligence provided by offline RL is contained by the dataset (Silver et al., 2021).

4.7 Software Development and Deployment

AI and IT software systems are (very) different. A piece of IT code can call APIs to achieve a certain goal, while, at least at the current stage, AI coding still needs a lot manual fine-tuning, for data, features, hyper-parameters, training methods, etc. There are already discussions about software and systems issues for machine learning systems. However, there are only a few papers discussing systems issues for RL, e.g., Agarwal et al. (2016), which call for more research and development (R&D). One factor is that ML systems are much more widely deployed than RL systems.

Sculley et al. (2014) discuss the hidden technical debt in machine learning systems. A technical debt refers to the long-term hidden costs accumulated from expedient yet suboptimal decisions in the short term. Besides normal code complexity issues in traditional software systems, ML systems incur at the system level enormous technical debts, e.g., boundary erosion, entanglement, hidden feedback loops, undeclared consumers, data dependencies, configuration issues, changes in the external world, and system-level anti-patterns. Potential solutions include refactoring code, improving unit tests, deleting dead code, reducing dependencies, tightening APIs, and improving documentation.

Agarwal et al. (2016) identify the following failures when applying contextual bandits to real life problems: partial feedback and bias, incorrect data collection, changes in the environment, and weak monitoring and debugging. The authors design software abstractions to avoid such failures and other hidden debts, i.e., Explore to collect the data, Log the data correctly, Learn a good model, and Deploy it in the application. Then the authors design software modules to implement the abstractions: Client Library, Join Service, Online Learner, Store, Offline Learner, and Feature Generator. Agarwal et al. (2016) introduce the multi-world testing to improve the efficiency of A/B testing.

RLlib (Liang et al., 2018) is an RL library to achieve a composable hierarchy for distributed programming. RLLib Flow (Liang et al., 2021) treats distributed RL as a dataflow and targets for more efficient programming. Ray/RLlib aims for a production level library.

Amershi et al. (2019) discuss software engineering for machine learning, which would also be helpful for reinforcement learning. The authors illustrate nine stages of the machine learning workflow, namely, model requirements, data
collection, data cleaning, data labeling, feature engineering, model training, model evaluation, model deployment, and model monitoring. There are many feedback loops in the workflow, e.g., between model training and feature engineering, and model evaluation and model monitoring may loop back to any previous stages. The authors also identify three major differences in software engineering for AI from that for previous software application domains: 1) it is more complex and more difficult to discover, manage, and version data; 2) different skill set for model customization and model reuse; and 3) AI components are less modular and more entangled in complex ways.

Sambasivan et al. (2021) discuss data cascades, i.e., compounding events from data issues cause negative, downstream effects, leading to technical debts over time. Paleyes et al. (2020) discuss deployment challenges for machine learning, w.r.t. data management, model learning, model verification, model deployment, and cross-cutting aspects. There is a conference dedicated to ML systems.

4.8 Business Perspectives

In this subsection, we discuss business perspectives of RL and AI in general.

RL is Promising!

In a Mckinsey Analytics report titled “It’s time for businesses to chart a course for reinforcement learning” (Corbo et al., 2021), the authors start with a story that RL helped reigning sailing Emirates Team New Zealand secure the fourth champion for 2021 America’s Cup Match. The authors then argue that RL will potentially deliver value in every business domain and industry; in the near-term, RL is particularly helpful for decision makings in design and product development, complex operations, and customer interactions; and for wide-scale adoption, we need a good learning algorithm with a reward function, a learning environment like a simulator, a digital twin or a digital platform, and compute power. RL becomes more accessible as technological advances w.r.t. algorithm efficiency, compute cost, and support from cloud computing. The authors give advices to leaders about how to start with RL: 1) find the right problem, solve the challenges not addressed by traditional methods; 2) consider compute costs upfront; 3) future-proof the simulator or digital twin for RL; 4) human in the loop, to improve humans’ performance, and to leverage experts’ domain knowledge; 5) identify and manage potential risks, such as explainability and ethical concerns.

In a Harvard Business Review article, Hume and Taylor (2021) predict that RL is the next big thing, list tough problems companies are addressing, e.g., trade execution platform for multiple strategies, test schedules for business partner devices, recommendation engine, financial derivative risk and pricing calculations, data center cooling, and order dispatching, and suggest the way to spot

https://mlsys.org
an opportunity for RL: make a list, consider other options, be careful what you wish for, ask whether it’s worth it, and prepare to be patient.

In an MIT Technology Review article, Heaven (2021) discusses that in supply chains, simulations, digital twins, together with AI, in particular, deep RL, can help improve visibility, balance efficiency and resiliency, conduct counterfactual or what-if analysis, and undergo stress tests, to help mitigate the negative effect of disruptions, in particular, during the pandemic. The article mentions that David Simchi-Levi said “a million dollars and 18 months can give you many of the benefits”.

**There are Still Issues for ML Systems Though.**

In an Andreessen Horowitz blog, Casado and Bornstein (2020) argue that AI creates a new type of business, combining both software and services, with low gross margins, scaling challenges, weak defensive moats, caused by heavy cloud infrastructure usage, ongoing human support, issues with edge cases, the commoditization of AI models, and challenges with data network effects. The author presents practical advices for founders: 1) eliminate model complexity as much as possible, 2) choose problem domains carefully to reduce data complexity, 3) plan for high variable costs, 4) embrace services plan for change in the tech stack, and 5) build defensibility the old-fashioned way.

Ng (2020) discusses how to bridge AI’s proof of concept to production gap w.r.t. small data, generalization and change management. Ng (2020) presents the ways to manage the change the technology brings: budget enough time, identify all stakeholders, provide reassurance, explain what’s happening and why, and right-size the first project, and argue that key technical tools are explainable AI and auditing. Ng (2020) discusses that production AI projects require more than ML code, e.g., data verification, environment change detection, data and model version control, process management tools and detect model performance degradation.

Ng (2021) argues that AI system = Code + Data and MLOps’ most important task is to make high quality data available through all stages of the ML project lifecycle, including scoping (decide on problem to solve), data (acquire data for model), modelling (build/train AI model), and deployment (run in production to create value). Ng (2021) discusses that model-centric AI focus on the question: “How can you change the model (code) to improve performance?” , while data-centric AI focus on the question: “How can you systematically change your data (input x or labels y) to improve performance?” . Ng (2021) argues that an important frontier is to build MLOps tools to make the process of data-centric AI efficient and systematic.

**AI∞, AIx, and AIZero**

For the current practice in AI, we make the following categorization: AI∞, AIx, and AIZero. Many deep learning, or big data methods, like AlexNet, relies on huge amount of labelled data. Model-free RL interacts with the environment
online or offline to collect a huge amount of training data. We classify them as AI∞, which requires significant manual efforts or interactions with the physical system to generate training data. When there is a perfect model, we can build a perfect simulator to generate training data, in a digital or virtual world, which is much less costly than in a physical world. AlphaGo Zero/AlphaZero and those dynamic systems with perfect partial differential equations are in this category. We classify them as AIZero, i.e., once the data generator is set up, it can generate data without manual effort, and without the cost of interacting with the physical system. Model-free RL for Atari games, e.g., with ALE, appears as AI∞ for the agent. However, for the whole system, we can say it is AIZero, since we have a perfect simulator. There are ways to help improve data efficiency, e.g., simulation, digital twins, self-supervised learning, and for RL in particular, intrinsic motivation, auxiliary signals, and model-based methods. We call such approaches as AIx, where x is a number between 0 and ∞, indicating the degree of inaccuracy of the model involved, or the amount of effort of “manual” collecting of data, or the amount of effort of interacting with physical systems. Admittedly, x is only loosely defined. AIx approaches AIZero as the underlying models approach perfect. GPT-3 is in AIx. Since InstructGPT involves human feedback, it is a combination of AI∞ and AIx. AlphaGo involves human demonstration data and a perfect model/simulator, so it is a combination of AI∞ and AIZero.

Considering the Gartner Hype Cycle, arguably, AlexNet in 2012 was in the stage of Technology Trigger. Shortly after AlphaGo, it reached Peak of Inflated Expectation, with bubbles from all sorts of fundings. It may be in Trough of Disillusionment now. We are witnessing that deep learning, RL and AI in general are making steady progress, as more and more scenarios moving from AI∞ to AIx and some approaching AIZero. Consequently, AI gradually goes into Slope of Enlightenment and Plateau of Productivity.

4.9 More Challenges
As illustrated in Figure 3, there are many more important topics, of which we only mention a few briefly in the following.

Bandits appear as the most mature techniques in RL. We refer readers to a paper on contextual bandits with real life results (Li et al., 2010) and a recent book (Lattimore and Szepesvári, 2018).

Exploration vs exploitation is a fundamental tradeoff for any RL algorithm. We refer readers to a survey (Li, 2012) and a recent blog (Weng, 2020).

Multi-agent RL (MARL) is the integration of multi-agent systems (Shoham et al., 2007; Hernandez-Leal et al., 2019; Zhang et al., 2021a) with RL. It is at the intersection of game theory (Leyton-Brown and Shoham, 2008) and RL/AI. Multi-agent systems are a great tool to model interactions among agents, for competition, cooperation and a mixture of them, with rich applications in human society. Besides issues in RL like sparse rewards and sample efficiency, there

\[^{19}\text{Admittedly, topics like bandits, exploration, explainability are worth more discussions.}\]
are new issues like multiple equilibria, and even fundamental issues like what is
the question for multi-agent learning, and whether convergence to an equilib-
rium is an appropriate goal, etc. Consequently, multi-agent learning is challeng-
ing both technically and conceptually, and demands clear understanding of the
problem to be solved, the criteria for evaluation, and coherent research agendas
(Shoham et al., 2007, Hernandez-Leal et al., 2019, Zhang et al., 2021a) are recent surveys about multi-agent RL. Papoudakis et al. (2019) survey non-
stationarity in multi-agent deep RL.

Hierarchical RL (Pateria et al., 2022) is a way to learn, plan, and represent
knowledge with temporal abstraction at multiple levels, with a long history, e.g.,
options (Sutton et al., 1999). Hierarchical RL is an approach for issues of sparse
rewards and/or long horizons, with exploration in the space of high-level goals.
The modular structure of hierarchical RL approaches is usually conducive to
transfer and multi-task learning. The concepts of sub-goal, option, skill, and,
macro-action are related. Hierarchical planning is a classical topic in AI (Russell
and Norvig, 2009).

The major achievements in AI in the last ten years or so, in particular, with
deep learning, are criticized for lacking of logic and reasoning. Most deep learn-
ing approaches are finding correlations or associations, rather than causality or
interventions and counterfactuals. Neuro-symbolic approaches are promising to
encode logic in learning mechanisms. In the following, we directly quote from
two papers. “The burgeoning area of neurosymbolic AI, which unites classical
symbolic approaches to AI with the more data-driven neural approaches,
may be where the most progress towards the AI dream is seen over the next
decade.” (Littman et al., 2021) “How are the directions suggested by these open
questions related to the symbolic AI research program from the 20th century?
Clearly, this symbolic AI program aimed at achieving system 2 abilities, such
as reasoning, being able to factorize knowledge into pieces which can easily
recombined in a sequence of computational steps, and being able to manipu-
late abstract variables, types, and instances. We would like to design neural
networks which can do all these things while working with real-valued vectors
so as to pre-serve the strengths of deep learning which include efficient large-

scale learning using differentiable computation and gradient-based adaptation,
grounding of high-level concepts in low-level perception and action, handling
uncertain data, and using distributed representations.” (Bengio et al., 2021a)

Explainability and interpretability are critical for transparency, trust, fair-
ness, etc. Miller (2019) survey how people define, generate, select, evaluate,
and present explanations in philosophy, psychology, and cognitive science and
the implication for explainable AI. The major findings are: explanations are
contrastive, explanation are selected in a biased manner, probabilities probably
don’t matter, and explanations are social. See Lipton (2018), Murdoch et al.
(2019), Rudin et al. (2021) for discussions and surveys about interpretable ma-
chine learning. See some recent work on explainable RL, e.g., Amir et al. (2019),
Atrey et al. (2020), Gottesman et al. (2020), Hayes and Shah (2017), Huang
et al. (2019), Huber et al. (2021), and Sequeira and Gervasio (2020).

It is essential to consider RL for good. Safety is related; Thomas et al. (2019)
discuss how to prevent undesirable behavior of intelligent machines. Garcia and Fernández (2015) present a survey on safe RL. Brunke et al. (2021) survey safe learning in robotics, from the perspective from learning-based control to safe RL. Wiens et al. (2019) discuss how to do no harm in the context of healthcare, which may somewhat generalize to AI. RL/AI practitioners, esp. those with AI power and resources and/or those dealing with high-stake issues like healthcare and autonomous driving, may need to take a “Hippocratic oath” or even go under stricter regulation. Russell (2019) discusses human compatible AI. Mitchell (2020) present a guide for thinking humans for AI. Generally and technically, this is related to multi-objective and constrained RL. See e.g. Szepesvári (2020a) and Szepesvári (2020c).

There are important topics, like sample efficiency, credit assignment, generalization (Kirk et al., 2021; Zhang et al., 2021b), which are discussed explicitly or implicitly in other sub-sections, as well as collective intelligence (Millhouse et al., 2021), evolution (Salimans et al., 2017; Ridley, 2015), etc. See Levine (2021) for a discussion about real world RL.

Before ending, let’s pose a question: How to select RL algorithms?

There are more and more interests in RL from academia, industry, governments, and venture capitals (VC). The question about RL algorithm selection may be from a student wanting to try a toy example/benchmark, or from a company planning to set up a prototype to see how RL works, or from a government working on an AI project like smart city, or from entrepreneurs thinking to build a startup leveraging the potential of RL.

There are so many algorithms, w.r.t. many dimensions, like on/off policy, model-free/based, online/offline, value function/policy optimization, exploration methods, etc. There may also be considerations for representation, end-to-end or not, auxiliary or un/self-supervised reward, prior knowledge, meta-learning, hierarchical, multi-agent, causal, symbolic, relational, explainable, safety, robustness, AI for good, etc., some of which are at the frontier of research actually.

Some factors may not be hard to characterize to select some type(s) of algorithms for certain problems. Some may be non-trivial. Some factors may be critical for making RL practical, like sample efficiency and safety.

Are there general, intuitive, maybe “rule-based”, guidelines for selecting RL algorithms? How about algorithms of the same/similar type, e.g., how to select among A3C, DDPG, PPO, SAC, TD3? Rather than trying everything, are there any refined suggestion? Or we are not there yet, i.e., we still need to wait for better algorithms?

Badia et al. (2020) and Laroche and Féraud (2018) use bandits to choose parameterized algorithms. Benchmarking/comparison papers may be helpful, e.g., Duan et al. (2016), Mahmood et al. (2018), Colas et al. (2019) and Agarwal et al. (2021). RL calls for an answer to the question: How to select RL algorithms?
5 Discussions

There are stunning news like AlphaGo and some successful applications in production. For research in RL for real life, there are growing interests with exciting achievements, attempting to address challenges as we discussed. However, there is still the question: Why has RL not been widely adopted in practice yet? Here is an attempt to answer it. And we look forward to more discussions in this vein.

One key issue is, RL does not have an “AlphaGo moment” in practice, and does not have a killer application yet. AlphaGo was a headline news worldwide. However, it appears that it does not have direct, significant business value. We have witnessed various successes applying RL in practice. However, there is not something for RL equivalent to face or speech recognition for deep learning yet. Will the nuclear fusion be a killer application for RL? Maybe. But likely not, since nuclear fusion requires huge resources to work on, harder to access than thousands of GPUs. However the success definitely shows the power of RL, and will attract more attention to RL.

A fundamental issue is there are still challenges with theories, algorithms and implementations. Real life problems may have too large action spaces for the current RL algorithms to handle. Off-the-shelf algorithms may not apply to real life problems directly, and still need significant fine-tunings from RL experts. We still encounter technical debts in software engineering and system deployment for RL, which is still in the early stage for research and development (R&D), partly as a consequence of not having many deployed RL systems yet. RL calls for better theories and algorithms as always, and more and deeper integration with real life applications and more deployed systems.

The R&D of RL projects requires considerable resources, including talents, compute, and funding, which are still insufficient. RL calls for more investments. Considering the current achievements RL has made in practice, such investments still need long-term thinking and the spirit of trial and error.

It is normal for a new technology to be adopted slowly, esp. by traditional industrial sectors. Should the technical route for RL be RL+ or +RL? With RL+, an RL expert leads the project, involving domain experts; whereas with +RL, RL experts need to collaborate with domain experts. It is likely +RL. Ideally experts have deep understanding of both RL/AI and domain knowledge. It is relatively easy to have such versatile experts for areas like recommender systems and robotics, since many AI people are working in these areas. However, for areas without many AI experts yet, it may be more practical for domain experts to have some knowledge of RL/AI, e.g., with the capability of managing an RL/AI application project, and coordinating RL/AI experts to help solve RL/AI problems abstracted from the problem, providing technical details of domain knowledge to RL/AI experts. This applies particularly to domains not easy for an RL/AI expert without sufficient background to have a decent understanding quickly, e.g., drug design, retrosynthesis, genetics, or arts. RL calls for more interdisciplinary education and training, or collaborations.

An AI project, esp. an RL one, is in stark contrast with an IT project,
in that it is necessary for all people involved in an RL/AI application project, from engineer to CEO, to have some knowledge of RL/AI. This is natural for technical people. For management people, with decent knowledge of RL/AI, it is easy for them to appreciate the potential and understand the challenges of the technology, and it is convenient for them to communicate with technical people. One issue is, the learning curve for RL is much steeper than for deep learning, for both concepts and technical details. RL calls for more education and training, esp. for non-technical people.

Similar to an AI business, an RL business may also be a combination of software and service, with low gross margins, scaling challenges, and weak defensive moats. RL calls for understanding of, respect for, and if possible, innovations in, the business model.

We see a big chicken-egg problem here: no killer application, insufficient appreciation from higher management, insufficient resources, insufficient R&D, slow adoption, then, as a result, non-trivial to have a killer application. There are underlying challenges from education, research, development and business.

Figure 4: Why has RL not been widely adopted in practice yet? The big chicken-egg loop: no killer application, insufficient appreciation from higher management, insufficient resources, insufficient R&D, slow adoption, then, as a result, non-trivial to have a killer application. There are underlying challenges from education, research, development and business. The status quo is actually much better, having many success stories. With challenges, RL is promising.
The status quo is actually much better than this negative feedback loop, thanks to those people and organizations who are forward looking and venture their belief in the potential of reinforcement learning. There are companies making big investments in RL, like DeepMind, Google, Microsoft, Facebook, OpenAI, Nvidia, Didi, just name a few. More and more researchers and engineers are interested in RL. There are also a few startups working on RL. And remember that, the killer application of face/speech recognition for deep learning was born out of the last AI winter, in particular, for (deep) neural networks. We are thus positive, although reinforcement learning is not quite there yet for the prevalence of real life applications.

Before closing, we attempt to answer the question: When is RL helpful?

In general, RL can be helpful, if a problem can be regarded as or transformed to a sequential decision making problem, and states, actions, and (sometimes) rewards can be constructed. RL is helpful for goal-directed learning. RL may help to automate and optimize previously manually designed strategies. The rate of success expects to be higher if a problem comes with a perfect model, a high-fidelity simulator, or a large amount of data.

For the current state of the art, RL is helpful when big data are available, from a model, from a good simulator/digital twin, or from interactions (online or offline). For a problem in natural science and engineering, the objective function may be clear, with a standard answer, and straightforward to evaluate. For example, AlphaGo has a perfect simulator and the objective is clear, i.e., to win. Good models/simulators usually come with many problems in combinatorial optimization, operations research, optimal control, drug design, etc. In contrast, for a problem in social science and arts, usually there are people involved, thus the problem is influenced by psychology, behavioural science, etc., the objective is usually subjective, may not have a standard answer, and may not be easy to evaluate. Example applications include education and game design. Recommender systems usually have bountiful data, so there are successful production systems. However, there are still challenges for those facing human users. Recent progress in RL from human feedback has shown its benefits in human value alignment. Concepts like psychology, e.g. intrinsic motivation, flow and self-determination theory, may serve as a bridge connecting RL/AI with social science and arts, e.g., by defining a reward function.

With challenges, we see great opportunities ahead for reinforcement learning.

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