https://arxiv.org/ftp/arxiv/papers/2202/2202.08444.pdf

Domain adaptation, task adaption
Domain generalization, task generalization
Adaptation refers to its ability to learn faster without re-training from scratch and generalization refers to its ability to extrapolate beyond the learned knowledge to tackle unseen environments.

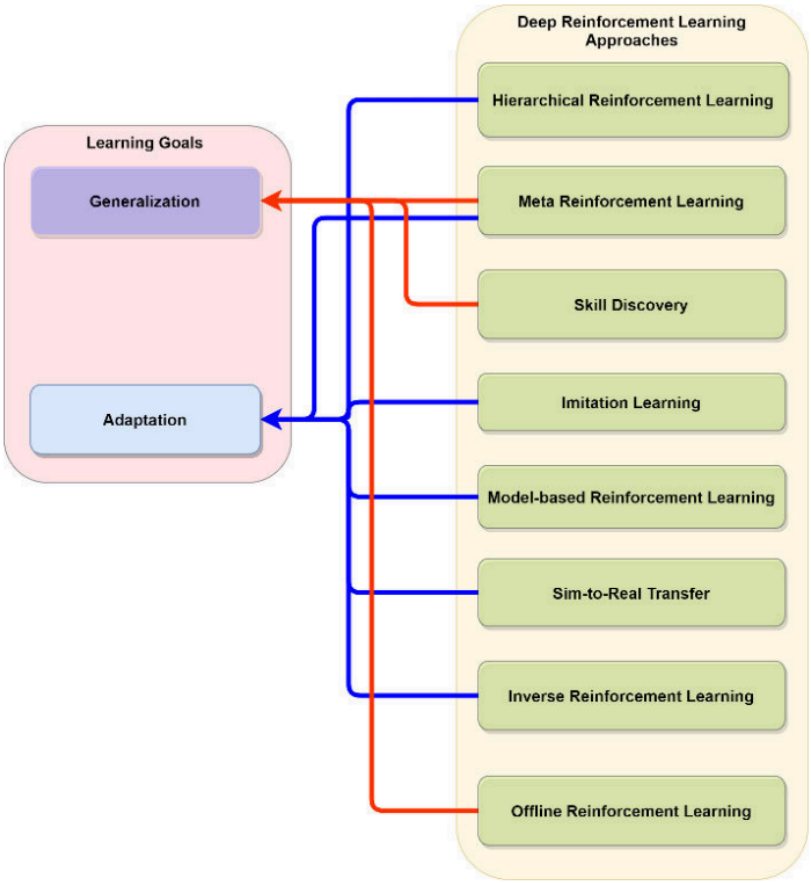
- Used as learning goals to evaluate algorithm's learnability

Markov Decision Process (MDP):

- (S, A, p_s, r)
- S: discrete or continuous state space
- A: discrete or continuous action space
- p_s: transition function
- r: reward function
- P_s and r are used to model the environment

Policy

- pi(a | s)
- Defines behavior of an agent by mapping a state s_t in S to an action a_t in A
- Deterministic or stochastic (preferred)



Hierarchical Reinforcement Learning

- Solve complex problems/ tasks that constitute simpler related problems/ tasks
- Transition policy gradient update for 2 level hierarchical network
    - Manager network that learns latent state- space and sets goals
    - Worker network that produces primitive actions based on goals from manager
- Multi level reasoning: method for learning hierarchy of policies
    - Low level policies: taking actions in environment
    - High level policies: planning long term decisions
    - High sample efficiency by training agent off- policy for complex tasks like robotic locomotion and object manipulation in simulation
- Priors for capturing learned knowledge by low level policies in a simple environment which can be transferred to a similar problem in a more complex environment
- Tackled problem of sparse reward using self supervision: efficient intrinsic option discovery to obtain higher rewards for the task

Meta Reinforcement Learning

- Learning to learn to generalize to unseen tasks/ domains
- Achieve faster adaptation to unseen tasks without learning from scratch by utilizing past experience

- Update rule defined in learning algorithms require re- iterative approach to tune parameters for each task
    - Meta learning provides a way to learn the rules for learning
    - Gradient based update in standard meta learning methods are expensive, degradation in generalization performance (ability to learn after given number of updates)
- Meta objective's constraint to similar geometry as of the learner
    - Bootstrapped to assimilate information about learning dynamics into meta-objective
- Meta objective's limited ability to generalize within given number of steps and failing to incorporate future dynamics
    - Minimizing distance to bootstrapped target using KL divergence

Skill Discovery

- Skill: latent conditioned policy that can be trained to perform useful tasks in a sparse/ unknown reward environment
- Variational inference based option discovery method for training agent to discover and learn skills through environment interaction without needing to maximizing cumulative reward
- Introduced a novel hierarchical RL algorithm which is capable of learning in a continuous, low level, latent space
    - Model capable of predicting output of learned skills
    - Crucial role in solving more complex tasks at a higher level
- Task generation is a major challenge for achieving multi task solving ability by an agent
- Priors help in deciding which skill is more important to explore while performing a particular action

Imitation Learning

- Agent to learn by observing an expert demonstrating the required task
- Off- policy Actor- critic algorithm that focuses on learning to imitate the agent's past good experiences (replay buffer)
- Effective way to solve autonomous driving by learning from human driving demonstrations
    - Allows agent to learn the preferences and goals of humans in a safe manner
- Distributional shift is a fundamental problem in imitation learning
    - Gives rise to causal misidentification effect that leads to setting wrong correlation between actions and their causes
    - Algorithm that learns mapping from causal graphs to the policies and then utilizes knowledge of experts to select correct policy for target tasks
- Providing high confidence bound on agent's performance with respect to expert's demonstration is a less- explored area
    - Most use Bayesian Inverse RL to measure reward uncertainty and error over policy generalization

    - Suffers from complex computation of MDPs leading to hindrance against safety and efficiency of model in unknown MDPs or high dimensional problems
    - Providing preferences over goals
- Generative Intrinsic Reward driven by Imitation Learning: better than expert performance from one expert demonstration
    - VAE to generate diverse future states and corresponding action latent variables
- Confidence aware imitation learning if expert demonstrations are insufficient (learned policies are suboptimal)
    - Learns policy and confidence value for every state action pair in expert's demonstration

Model based RL

- Model free RL has shown tremendous success for solving tasks in simulated environment but they are highly sample inefficient
- Model based is sample efficient by performing policy optimization against learned dynamics of environment (can be used in real world)
- SimPLE algorithm
- Online RL typically requires iterative collection of experiences during training
    - Deployment efficiency: records number of increments in the data collection policy during training
    - Behavior Regularized Model Ensemble: aims to learn an ensemble of environment dynamics models

Sim2Real Transfer

- Develop a technique that allows agent to adapt to an unseen domain
    - Train in sim and test in real
    - Domain randomization
    - Complexities in real domain such as contact dynamics, soft bodies, and hidden information in general prevent optimal transfer
- Algorithm that can learn disentangled representation of the environment's generative factors and utilize this information to learn a robust source policy that can be transferred to target domain (real world)
- Most modern RL involves robotics manipulation on rigid objects but deformable objects is an important yet underexplored area
    - Large configuration space change involved in manipulating deformable objects

Inverse RL

- Understanding objectives and rewards of agent by observing its behavior
    - Infers reward function from rollouts of expert policy -> policy improvement and generalization
    - Knowledge of reward is a primary goal -> apprenticeship is commonly used to acquire such policy learning from expert
- Use apprenticeship learning to utilize prior knowledge and experiences from actions of an expert to derive a probability distribution over space of reward functions

- Fails to adapt to locally consistent constraints
    - Divide complex task into several subtasks with corresponding set of local constraints

Offline RL

- Policy learning from pre- collected dataset of trajectories/ experiences for tasks where agent is not allowed to interact with environment
    - Overcome practical limitation of online RL such as expensive interaction
- Poor off policy evaluation causes inaccurate Q value estimation
    - Distribution shift: causes evaluation error and propagates to evaluation step of current policy
    - Iterative error: error between Q estimate's errors and tend to overestimate each step, reusing data causes amplification of such error

Discussion

- Distributional shifts in data between training and testing domain is one of the primary causes behind shortcomings in RL research
    - Most focus on task adaption/ domain adaptation but important to focus on generalization
- Large, diverse datasets have allowed application of Offline RL to achieve generalization
    - Hard to scale because of longer training time and mostly applied to simulation or controlled environments
    - Need real world datasets and incorporate contextual information about environment and other agents
- Meta RL requires less training time to achieve faster adaptability/ generalizability
    - Only in controlled environments
    - Measure their reliability before deployed in open world environments
    - Skill discovery algorithms have also demonstrated ability to perform generalization
- Autonomous vehicles are an example of open world environment
    - Current RL research fails to incorporate notion of safety for undesirable situations