Reinforcement Learning and Beyond
Part II: Transfer Learning in RL

Section 3: Conclusions and Future Work

Outline

- Selection of future challenges
  - Towards a theoretical foundation of transfer in RL
  - Enabling fully autonomous transfer
  - Constructing effective task learning sequences
- Concluding summary

Theoretical Foundation

- RL is more complex than supervised learning
- Transfer in RL introduces specific scenarios and issues
- Recent theoretical results in RL shows that it has strong connections with statistical learning theory results (see (Munos&Szepevari, 2008))
- Recent theoretical results in TL in supervised learning shows the effectiveness of TL w.r.t. single task learning
  - Inductive bias learning
  - Multi-task learning

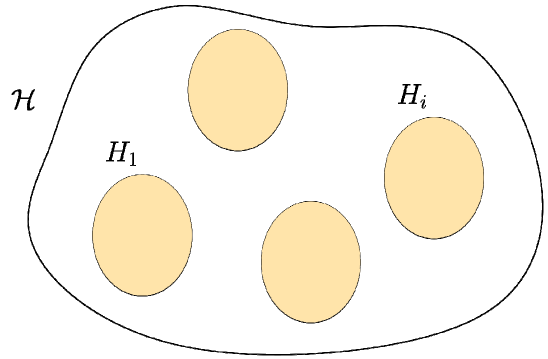
State of the Art

	Supervised Learning	Reinforcement Learning
Single Task	(Vapnik&Chervonenkis, 1971)	(Munos&Szepesvari, 2008) (Farahmand et al., 2008)
Multi Task	(Baxter, 2000) (Ben-David&Shuller, 2008)	**Nothing!**

Inductive Bias Learning

- *"A model of inductive bias learning"* (Baxter, 2000)
- Scenario
  - Distribution $\mathcal{Q}$ over task space $\mathcal{P}$
  - Training set m samples from each of n tasks
- *Objective*: find a hypothesis space H which contains good hypotheses for all the tasks in $\mathcal{P}$ on average (according to distribution $\mathcal{Q}$)

Inductive Bias Learning



Extension of complexity measures (e.g., VC, covering numbers) to the set of hypothesis spaces $\mathcal{H}$

Inductive Bias Learning

- If
  - enough tasks are provided to the learner and
  - enough samples per task are collected
  - the set of hypothesis spaces is not too big
- Then
  - The generalization error of the hypothesis space H can be bounded on new tasks drawn from $\mathcal{Q}$
  - The generalization performance is better than learning independently
  - The number of samples decreases with the number of tasks

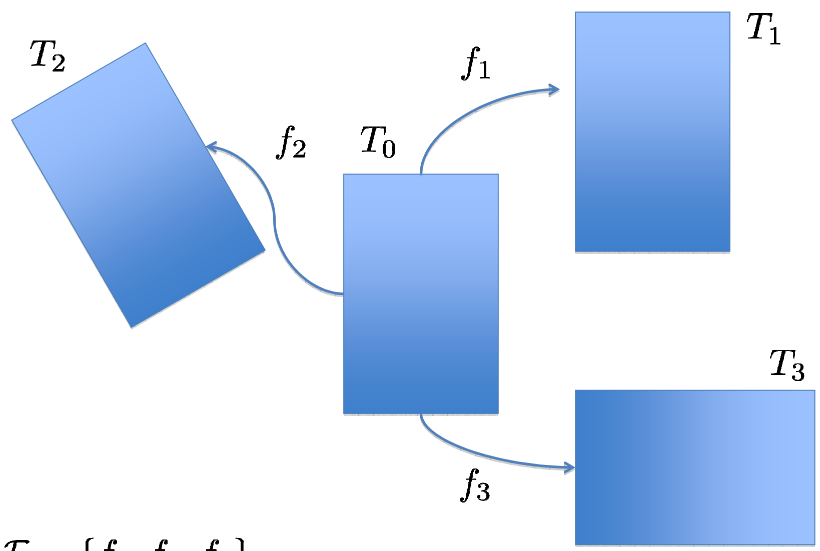
Inductive Bias Learning in RL

- Pros
  - The scenario could be easily adapted to RL domains (distribution of MDPs/value functions)
  - RL could be decomposed in a sequence of supervised learning problems (e.g., FQI)
- Cons
  - Not straightforward generalization of Baxter's result across different iterations (e.g., FQI, policy improvement)
  - Similar MDPs does not imply similar solutions

Transformation-Based MTL

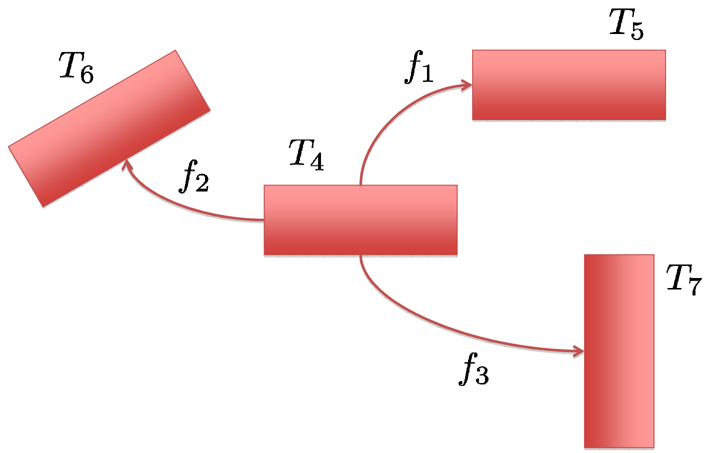
- *"A Notion of Task relatedness Yielding Provable Multiple-task Learning Guarantees"* (Ben-David &Shuller, 2008)
- Scenario
  - Multi-task learning on n tasks
  - Training set: m samples from each of n tasks
  - Assumption: all the tasks pair-wise f-related, with f a transformation in a set of possible transformations $\mathcal{F}$
- *Objective*: given a target task, use all the samples to find the *high-level* characteristics of the solution and use the target samples to learn the *task-specific* solution

Transformation-Based MTL



$\mathcal{F} = \{f_1, f_2, f_3\}$

Transformation-Based MTL

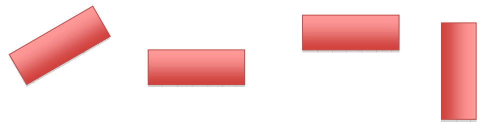


$\mathcal{F} = \{f_1, f_2, f_3\}$

Transformation-Based MTL

- *Phase1:* use all the samples to identify which class the target task belongs to

- *Phase2*: use only samples of the target task to identify the best solution



Transformation-Based MTL

- If
  - enough samples per task are collected
  - enough target samples are collected
  - if the set of transformations is not too big
- Then
  - The performance for (any!) target task is better than learning independently
  - The number of samples decreases with the number of tasks

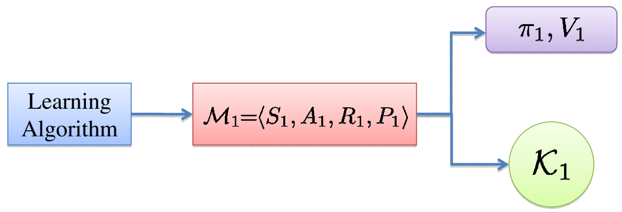
Transformation-Based MTL in RL

- Pros
  - RL could be decomposed in a sequence of supervised learning problems (e.g., FQI)
- Cons
  - Not straightforward definition of transformation in RL domains
  - Not straightforward generalization of Ben-David's bounds across different iterations

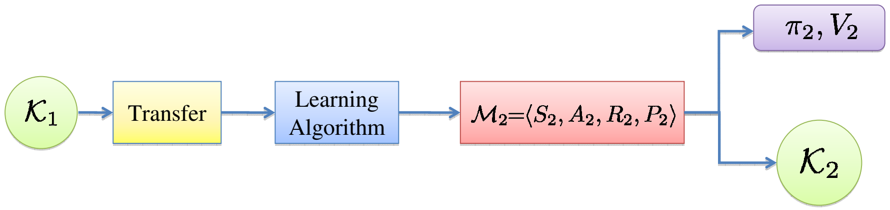
Theoretical Foundation

- Similarities of RL and supervised learning
- Promising line of research
- Several issues still unsolved (even in TL in supervised learning!)

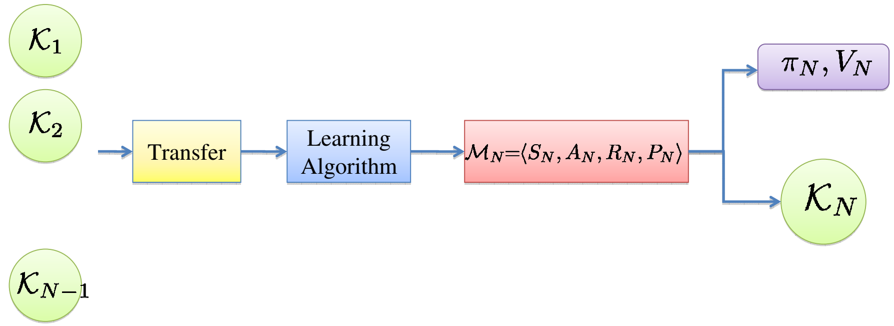
Fully Autonomous Transfer



Fully Autonomous Transfer



Fully Autonomous Transfer



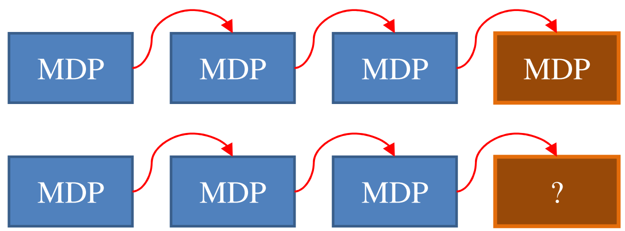
Fully Autonomous Transfer

- The full transfer problem
  - Different SxA
  - N-to-1 transfer
- Challenges
  - Learn the mapping
  - Select source tasks
  - Transfer effectively

Constructing Task Sequences [Taylor, 2009]

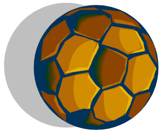
- Humans can selecting a training sequence
- Results in faster training / better performance

- Meta-planning problem for agent learning



Useful Information for Sequence Construction

- Common Sense
  - Soccer balls roll after being kicked
  - Friction reduces an object's speed



- Domain Knowledge
  - It is easier to complete short passes than long passes
- Algorithmic Knowledge
  - State space size can impact learning speed