Reinforcement Learning and Beyond
Part II: Transfer Learning in RL

Dr. Alessandro Lazaric (Alex)
Dr. Matthew E. Taylor (Matt)

Outline

1. Transfer in AI and Machine Learning
   – Matt
2. Transfer in Reinforcement Learning
   – Alex, Matt
3. Conclusions
   – Alex

Objectives

• Classification of approaches
• TL difficulties in RL domains
  – **When**: definition and discussion of different transfer problems in RL domains
  – **What**: overview of popular approaches
  – **How**: augmenting RL algorithms with TL
• Future research directions

sequel.futurs.inria.fr/lazaric

teamcore.usc.edu/taylorm

Reinforcement Learning and Beyond
Part II: Transfer Learning in RL

Section 1: Transfer in AI and Machine Learning
The Theory of Transfer

“Transfer of learning occurs when learning in one context enhances (positive transfer) or undermines (negative transfer) a related performance in another context.”

Motivations for TL

• Learning *tabula rasa* can be extremely slow
  – Lots of data / time may be needed
  – Every algorithm has biases: why use an uninformed bias?

• Humans always use past knowledge
  – What knowledge is relevant?
  – How can it be effectively leveraged?

Example: Sebastian Thrun

• Explanation-Based Neural Network Learning: A *Lifelong Learning* Approach

• Is Learning the nth Thing any Easier than Learning the First?
  – NIPS, 1996

• Learning to Learn
  – Edited volume (with Lorien Pratt), 1998

Example: Rich Caruana

• *Multitask* Learning: A Knowledge-Based Source of Inductive Bias
  – ICML 1993

• Learning Many Related Tasks at the Same Time with Backpropagation
  – NIPS 1995

• Algorithms and Applications for Multitask Learning
  – ICML 1996

• Multitask Learning

Example: Matt’s & Alex’s work
Towards Transfer Learning

- ML-COLT ’94 Workshop on Constructive Induction and Change of Representation
  - Towards autonomy
  - Generate / modify representations automatically
- NIPS ’95 Workshop on Learning to Learn: Knowledge Consolidation and Transfer in Inductive Systems
  - Capitalize on previously acquired domain knowledge

Challenges and Goals

“Transfer [learning] is a sequential process that influences the performance of learning through the reuse of structured knowledge [collected on previous tasks] and improves the behavior of the agent on new related tasks.”

Pat Langley
(Workshop on Structural Knowledge Transfer for Machine Learning, ICML 2006)

More recent TL workshops

- Inductive Transfer: 10 Years Later
  - NIPS 2005
- Structural Knowledge Transfer for Machine Learning
  - ICML 2006
- Transfer Learning for Complex Tasks
  - AAAI 2008

Challenges

- Structured Knowledge
  - Definition
  - Collection
  - Reuse
- Transfer process
- Task-independent Metrics
- Task Relatedness
- Negative Transfer
## An Overview of TL in ML

- Many names
  - Learning to Learn
  - Meta-learning
  - Lifelong Learning
  - Continual Learning
  - Multi-task Learning
  - Inductive Transfer Learning

## Hierarchical Bayes

- All the tasks are generated according to a fixed distribution
- Define a hyper-distribution over the task distribution
- Compute the distribution parameters according to the samples collected over all the tasks

### Hierarchical Bayes

- **Techniques**
  - Hierarchical Bayes
  - Regularized Regression
  - Neural Networks
  - Graph Integration

### Hierarchical Bayes

- **Multi-Task Gaussian Processes**
  - Linear functions $f_t(x) = w^T_t x$
  - Task distribution $w_t \sim N(\mu_{t,\tau}, C_{t,\tau})$
  - Hyper-prior $(\mu_{t,\tau}, C_{t,\tau}) \sim N\left(0, \frac{1}{\tau^2}\right) I W(\tau, I)$
  - Inference problem: given $m$ samples from $n$ tasks
    - Posterior $\tilde{w_t}, \tilde{C_t}$
    - Parameters $\mu_{t,\tau}, C_{t,\tau}$
  - Given the parameters it can be used also to improve the performance on new tasks
Hierarchical Bayes

- MTL with Dirichlet Process (DP) priors
  - Tasks often are not homogeneous and belong to different classes
  - Dirichlet Process automatically clusters tasks into classes
  - Define hyper-priors over the DP parameters
  - Use all the samples to refine the DP parameters
  - Given the parameters it can be used also to improve the performance on new tasks

Regularized Regression

- Single-task Regularized Regression
  \[ \sum_{i=1}^{n} \text{loss}(y_i, f(x_i)) + \lambda \|f\|_{\text{norm}} \]
  where \( \| \cdot \|_{\text{norm}} \) is a suitable norm (e.g., L2 for linear regression)
- Multi-task Regularized Regression
  \[ \sum_{i=1}^{n} \sum_{j \neq i} \text{loss}(y_i, f_i(x_i)) + \lambda \|f\|_{\text{norm}} \]
  where \( \| \cdot \|_{\text{norm}} \) forces the tasks to be similar

Related Paradigms

- Lifelong Learning
  - Less clear task boundaries (spatial / temporal)
  - Prepare for anything
- Imitation / Demonstration Learning
  - Watching a similar agent or human
- Direct Human Advice
  - Action suggestion
  - Direct knowledge injection
- Shaping
  - Reward function
  - Human modifies reward function over time

Linear Multi-Task Regularization

\[ \sum_{i=1}^{n} \|\omega_i\|^2 \]

Task clustering (Evgeniou, 2005)

\[ \sum_{i=1}^{n} \sum_{j \neq i} \|\omega_i - \omega_j\|^2 \]

Graph regularization (Evgeniou, 2005)

\[ \sum_{i=1}^{n} \|\omega_i\|^2 \]
Goals

- Improve performance over non-transfer learning
  - Sample Complexity
- Jumpstart
- Learning speed
- Final performance
- Asymptotic Performance

How TL in RL relates to TL in general

- RL is the most general learning paradigm
  - Approximation
  - Exploration/exploitation
- More challenging than in supervised
  - Large number of scenarios
  - Many different types of knowledge can be transferred
  - Difficult to assess the contribution of transfer to the learning performance
- Many possible goals
- Many possible applications