Socio-Emotional Reward Design for Intrinsically Motivated Learning Agents

Thesis Defense
Ph.D. Program in Information Systems and Computer Engineering

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Outline

Problem
Approach
Emotion-based Intrinsic Rewards
Emerging Emotions
Socially-Aware Learning Agents
Conclusions
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Problem

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Conclusions
Problem

Reinforcement Learning (1/2)

- Simple navigation problem
  - *State*: agent location
  - *Actions*: movement
Reinforcement Learning (2/2)

- **RL main ideas** (Sutton & Barto, 1998; Kaelbling et al., 1996)
  - Objective: maximize the reward throughout time
  - Task: discover which actions maximize reward in each state
    - *e.g.*, using *Q*-learning (Watkins, 1989)
Problem

Challenges in RL

- **Assumptions** (Sutton & Barto, 1998; Kaelbling et al., 1996)
  - Fully observable environments
  - Infinite visits to all states and actions
  - Stationary environments

- **Agent limitations**
  - Limited perception and computational resources
  - Dynamic, unpredictable and unreliable environment
  - Demand for manual adjustments

- **Design assumptions too restrictive**
  (Littman, 1994; Loch and Singh, 1998; Singh et al., 1994)
Rewards are fundamental (Sutton & Barto, 1998; Kaelbling et al., 1996)

- Implicitly defines the agent’s task
- Impact on the learning time
- Impact on what is learned

Major challenge (Abbeel and Ng, 2004; Ng and Russell, 2000; Sorg et al., 2010a)

- Build reward mechanisms so the task is learned efficiently
- Flexible and robust
- Enhance agent’s autonomy
“Design reward mechanisms for RL agents that are able to alleviate their inherent perceptual limitations and make them operate in a wide variety of domains without the explicit intervention of others or relying on expert or domain knowledge about a particular task.”
Outline

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Conclusions
Sources of Information

- Agent has access to several sources of information
  - Perception, reasoning, learning, etc.
Intrinsic Motivation

- Intrinsically Motivated RL (Singh et al. 2009, 2010; Sorg et al. 2010)
  - Agent learns with intrinsic rewards
  - Fitness: measures performance
  - Mitigates computational limitations of learning agents
Approach

Inspiration

- Parallel with biological organisms
  - Limited perception and resources
  - Dynamic, unpredictable and unreliable environment

- Natural motivational mechanisms
  - Shaped by evolution
  - Provide adaptive advantages

- Social mechanisms
  - Cooperation in inherently competitive environments
“We focus on the **role of emotions** and also on the way **individuals interact and cooperate** with each other as a social group to **design more flexible and robust reward mechanisms** that **enhance the autonomy** of RL agents in both single and multiagent settings.”
Contributions

- Emotion-based Intrinsic Rewards
  - Role of emotions in decision-making
  - 4 emotion-based domain-independent reward features

- Emerging Emotions
  - Emergence of useful sources of information
  - Discuss relation with emotions

- Socially-Aware Learning Agents
  - Extend IMRL to multiagent scenarios
  - Socially-aware behaviors
Outline

Problem

Approach

*Emotion-based Intrinsic Rewards*

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Conclusions
Emotion-based Intrinsic Rewards

The Role of Emotions

- Studies show that emotions:
  - Basic and ancient survival mechanism
  - Beneficial adaptive mechanism for decision-making
  - Elicit physiological signals

- Absence of emotions
  - Impairs taking advantageous decisions

- How to provide emotion-based motivation?
Emotion-based Intrinsic Rewards

Appraisal Theories of Emotions

- Evaluation through appraisal
Emotion-based Reward Design

- **Major dimensions of appraisal** (Ellsworth & Scherer 2003, Leventhal & Scherer, 1987)
  - 4 domain-independent reward features
  - Evaluate agent’s history of interaction with environment
Emotion-based Intrinsic Rewards

Experiments

- Foraging scenarios
  - Each presents distinct challenge
  - Partially-observable
  - Compare performance emotion-based vs. fitness-based

Results
- Emotional agents outperform standard agents
- Careful consideration of emotional aspects
- Learn the intended task
- Overcome perceptual limitations
4 emotion-based reward features

- Novelty, Valence, Goal relevance and Control
- Domain-independent
- General-purpose guiding system for RL agents
- Mitigation of perceptual limitations

Departs from previous works within Affective Computing

- Domain-independent appraisal-based
- Does not alter RL algorithm
- Does not focus on a set of basic emotions
Outline

Problem

Approach

Emotion-based Intrinsic Rewards

**Emerging Emotions**

Socially-Aware Learning Agents

Conclusions
Answer the question:

"Are emotions the best candidate to complement the agents’ information processing mechanism?"
Emerging Emotions

**Optimal Sources of Information**

- Reward optimization using Genetic Programming (Niekum et al. 2010)
  - Population of reward functions
  - Evolved and evaluated according to agent’s performance
Emerging Emotions

Foraging Experiments

- Same foraging scenarios as before
  - Observe resulting evolved optimal rewards
  - Discover patterns in the reward functions’ expressions

- Results
  - Set of 5 informative signals
  - Fitness, relevance, advantage, prediction, frequency
  - Each signal can be used as an intrinsic reward feature
Emerging Emotions

PacMan Experiments

• Scenarios based on PacMan
  • Objective: validate emerged optimal sources of information
  • Different and much more complex scenarios
  • Limited perception

Results

GP-based agent outperformed standard agents
Learn the intended task
Overcome perceptual limitations
Emerging Emotions

Analysis

• Analyze emerged information signals
  • Compare the “kinds” of evaluation
  • According to appraisal theories of emotion

• Results
  • Informative signals provide similar evaluation
  • Share structural and dynamical properties
Emerging Emotions

Contributions

- Information-processing reward mechanism
  - Emerged by means of genetic programming
  - Domain-independent
  - Mitigation of perceptual limitations
- Relation with natural agents and emotions
  - Dynamic and structural connections with appraisal dimensions
  - Adaptive mechanism that allows for higher fitness
  - Reinforce the role of emotions in agents adaptation
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Conclusions
Socially-Aware Learning Agents

Motivation

- Extend previous research into multiagent settings
  - Shared environment
  - Each agent has its own goals
    - May be conflicting
  - Achieve cooperation

- Inspiration from social mechanisms
  - Living in group augments survival chances
  - Still there is competition for resources and power
  - Communicate intentions and evaluate each others actions
Socially-Aware Learning Agents

Cooperation in Nature

- Cooperation in competitive contexts

  - Need for affiliation
    - Altruistic behaviors despite momentary losses

  - Legitimacy signals
    - Signal socially-aware behaviors

  - Reciprocation mechanism
    - Evaluates “kindness” of others’ actions
Socially-Aware Learning Agents

Social Intrinsic Motivation

- Limited resource sharing scenarios
  - Internal and external social rewards
  - Evaluate appropriateness of behaviors towards social group
Socially-Aware Learning Agents

Social Experiments

- Limited resource and mutual dependency scenarios
  - 2 or 3 agents interact in the same environment
  - Limited perception
  - Agents learn and act individually, fitness is measured of the social group

Results

- Socially motivated agents outperformed "greedy" group
- Mostly homogeneous populations
- Emergence of "socially-aware" behaviors
Socially-Aware Learning Agents

Contributions

- Extend IMRL to multiagent scenarios
  - Social intrinsic motivation
    - Based on affiliation, social signaling and reciprocity
  - Emergence of “socially aware” behaviors
    - Trade-off immediate gains for future collaboration
    - Learned behaviors benefit whole group
  - Accordance with how cooperation thrives in nature
    - Existence of signaling mechanism
    - Reciprocation opportunities
    - Future interactions
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“We focus on the role of emotions and also on the way individuals interact and cooperate with each other as a social group to design more flexible and robust reward mechanisms that enhance the autonomy of RL agents in both single and multiagent settings.”
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Implications (1/2)

- RL and IMRL
  - Alleviate perceptual limitations and modeling effort
  - More autonomous, robust and flexible mechanisms
  - Novel approach for multiagent IMRL

- Affective Computing
  - Show the importance of emotion-based reward design
  - Independent of algorithm, not focused on set of basic emotions
  - Parallel with natural organisms
  - Importance of emotion-related information
Conclusions

Implications (2/2)

- Multiagent Systems
  - Relation with evolutionary game theory
    - Emergence of cooperation with relatedness and reciprocation
  - Signaling mechanism according to internal social standards
  - Emergence of cooperation by means of
    - Social pressures
    - Pure altruism
The End