Machine Learning and Artificial Intelligence for Autonomous Robots

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(Also, Cogitai Inc.)
A Goal of AI and Robotics
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Robust, **fully autonomous** agents in the real world
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How?
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- Build complete agents to perform increasingly complex tasks
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  - Complete agents: sense, decide, and act — closed loop
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    (Machine learning)
  - Interact with other agents  
    (Multiagent systems)
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“Good problems . . . produce good science”
Research Question

To what degree can autonomous intelligent agents learn in the presence of teammates and/or adversaries in real-time, dynamic domains?
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Research Areas

- Autonomous agents
- Multiagent systems
- Robotics
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- Machine learning
  - Reinforcement learning
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- Multiagent systems
- Robotics
- Machine learning
  - Reinforcement learning
  - Cogitai
RoboCup Soccer
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- Grand challenge: beat World Cup champions by 2050
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  - Incremental challenges, closed loop at each stage
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Drives research in many areas:
- Control algorithms; computer vision, sensing; localization;
- Distributed computing; real-time systems;
- Knowledge representation; mechanical design;
- Multiagent systems; machine learning; robotics
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- 400+ publications from simulation league alone
- 200+ from 4-legged league
- Dozens (at least) of Ph.D. theses
Robot Vision

- Great progress in computer vision
  - Shape modeling, object recognition, face detection...

- Robot vision offers new challenges
  - Mobile camera, limited computation, color features

- **Autonomous color learning** [Sridharan & Stone, ’05]
  - Learns color map based on known object locations
  - Recognizes and reacts to illumination changes

  - Object detection in real-time, on-board a robot
RoboCup@Home
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Reinforcement Learning

Supervised learning mature [TensorFlow]
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For agents, reinforcement learning most appropriate
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For agents, reinforcement learning most appropriate

- Foundational **theoretical** results
- Applications require **innovations** to scale up
RL Theory

Success story: Q-learning converges to $\pi^*$ [Watkins, 89]
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- Table-based representation
- Visit every state infinitely often
Function Approximation

In practice, visiting every state impossible

\[ s[t-1], a[t-1], Q(s,a) \]

\[ s[t], \quad r[t], \quad a[t] \]
Function Approximation

In practice, visiting **every state** impossible

Theoretical **guarantees** harder to come by
Applications: Towards a Useful Tool

- Backgammon [Tesauro, ’94]
- Helicopter control [Ng et al., ’03]
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- Invasive species management, wildfire suppression [Dietterich et al., ’13]
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- Google DeepMind beats human go champion, [Silver et al., ’16]
Selected RL Contributions

- Human interaction
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  - Advice, Demonstration
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  - Advice, Demonstration
  - Positive/Negative Feedback

[Knox & Stone, ’09]
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- Transfer learning for RL

- Curriculum Learning

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[Liebman et al., ’15]
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- TEXPLORE for Robot RL
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• TEXPLORE for Robot RL
  – Sample efficient; real-time
  – Continuous state; delayed effects
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  - Sample efficient; real-time
  - Continuous state; delayed effects

- Deep RL in continuous action spaces
Artificial Intelligence and Life in 2030

100 Year Study on AI: 1st Study Panel Report

Prof. Peter Stone*
Study Panel Chair
Department of Computer Science
The University of Texas at Austin
*Also Cogitai, Inc.

https://ai100.stanford.edu
“To support a longitudinal study of influences of AI advances on people and society, centering on periodic studies of developments, trends, futures, and potential disruptions associated with the developments in machine intelligence, and on formulating assessments, recommendations and guidance on proactive efforts.” (July 2014)
One Hundred Year Study: Timeline of Studies

AAAI Asilomar study

2015

Standing committee

Study panel

2020

Standing committee

Study panel

2115

Standing committee
One Hundred Year Study: Intended Audiences

Stanford Digital Archive

2015

Standing committee
Study panel

Convey results to multiple audiences

AI researchers
General public
Industry
Policy makers

Stanford University
Charge to the Inaugural Study Panel: Artificial Intelligence and Life in 2030

Identify possible *advances* in AI over next 15 years and their *potential influences on daily life*.

Specify *scientific, engineering, and legal efforts* needed to realize these developments.

Consider actions needed to shape outcomes for *societal good*, deliberating *design, ethical and policy challenges*.

Focus: *large urban regions* (typical North American city), grounding the examination of AI technologies in a context that highlights

▶ *potential influences on a wide variety of activities*
▶ *interdependencies and interactions among AI technologies*
Members of the Inaugural Study Panel
Artificial Intelligence and Life in 2030

Chair: Peter Stone, UT Austin

- Rodney Brooks, Rethink Robotics
- Erik Brynjolfsson, MIT
- Ryan Calo, University of Washington
- Oren Etzioni, Allen Institute for AI
- Greg Hager, Johns Hopkins
- Julia Hirschberg, Columbia
- Shivaram Kalyanakrishnan, IIT Bombay
- Ece Kamar, Microsoft
- Sarit Kraus, Bar Ilan
- Kevin Leyton-Brown, UBC
- David Parkes, Harvard
- William Press, UT Austin
- Julie Shah, MIT
- Astro Teller, X
- Milind Tambe, USC
- AnnaLee Saxenian, Berkeley
Structure

• Preface for context
• Executive Summary (1 page)
• Overview (5 pages)
• Introduction
  • Defining AI; Current research trends
• AI by domain
  • 8 areas with likely urban impact by 2030
  • Look backwards 15 years and forward 15 years
  • Opportunities, barriers, and realistic risks
• Policy and legal issues
  • Current status; Recommendations
• Lots of callouts in the margins
Areas of Focus in the Study Panel Report

Transportation
Home-Service Robots
Healthcare
Education
Public Safety and Security
Low-resource communities
Employment and Workplace
Entertainment

- hardware
- partnering with people
- building trust
- societal futures
- interpersonal interaction
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Summarizing callouts in the report
Artificial Intelligence and Life in 2030

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