Introduction into Imitation Learning

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1. Admin
2. Literature
3. What is Imitation Learning?
4. Applications of Imitation Learning
5. Problems with Reinforcement Learning
6. Problems with Supervised Learning
7. What does Imitation Learning add?

Admin

Before we start

- lots of reading
- knowledge of these is helpful:
  - ➡ foundations of probability theory
  - ➡ foundations of statistical machine learning
  - ➡ reinforcement learning
  - ➡ structured prediction
  - ➡ neural networks
- assessment: presentations or projects
- projects: programming (if you want to really learn)
  - ➡ project emphasis open applied research problems

This a block module, so **you have two options:**

1. presentation
   - ➡ presentation (end of the 1st or in the 2nd week)
   - ➡ write-up detailing the presented article, during the semester
   - ➡ compare with rival approaches
   - ➡ describe and defend extensions if any
   - ➡ small implementation is encouraged but not required

Deliverables

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2. project
   - ➡ briefly describe the task, research question and your plan (2nd week)
   - ➡ no slides necessary (unless you prefer)
   - ➡ implementation at your own pace during the semester
   - ➡ report detailing the approach and experiments
   - ➡ bi-weekly updates over skype or email

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- there is a list of tentative projects and presentation topics
- but you are encouraged to come up with your own ideas

Schedule

- 1st week, Oct. 8-12
  - ➡ 10:15-11:45 morning session
  - ➡ 13:15-14:45 afternoon session
  - ➡ first article presentations
  - ➡ no morning session on Friday - Erstifrühstück
- till Sat Oct. 13 23:59
  - ➡ inform via email whether you do a presentation or a project

Schedule

- 2nd week, Oct. 15-19
  - ➡ article presentations and project Q&A
  - ➡ consultations on the articles/projects
- rest of the semester
  - ➡ work on projects and writeups
  - ➡ updates via email/skype

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  - ➡ present the approach, include the glossed-over parts
  - ➡ try to formulate possible extensions
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- timeline
  - ➡ before Oct. 13: decide on the article
  - ➡ Oct. 15-18: time to discuss/ask questions
  - ➡ Oct. 15-19: in-class presentation
    (except 3 easier articles that, if selected, should be presented this week)
  - ➡ end of semester: final write-up due
    - try to formulate and defend possible extensions
    - include analysis of extensions if any
    - comparison to other methods and limitations

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- an implementation of a state-of-the-art algorithm for an NLP task
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    - ➡ compare to reasonable baselines
- timeline
    - ➡ before Oct. 13: decide on the project
    - ➡ Oct. 15-19: time to discuss/ask questions
    - ➡ Oct. 15-20: in-class project discussion (no slides necessary)
    - ➡ semester: bi-weekly updates if needed
    - ➡ end of semester: final report due
        - include all the experimental results and link to the code
        - structure like a conference paper (setting, prior work, why it matters, your approach, results, their analysis, limitations, future directions).

Evaluation

- presentation
  - ➡ 70% - quality of the presentation and extensions
  - ➡ 30% - quality of the final write-up
- project
  - ➡ 70% - quality of the implementation and results
  - ➡ 30% - quality of the final report

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  - 30% - quality of the final write-up
- project
  - 70% - quality of the implementation and results
  - 30% - quality of the final report
- more points for novelty and your ideas
- the effort is what mainly counts

After this course you should be able to:

- recognize tasks solvable with imitation learning
- map NLP and structured prediction problems to imitation learning
- understand deficiencies of some straight-forward approaches to IL
- solve problems with IL

Literature

- reinforcement learning
  - ➡ Sutton and Barto, "Reinforcement Learning", **2nd edition** 2018 `http://incompleteideas.net/book/the-book-2nd.html`
  - ➡ Szepesvari, "Algorithms for Reinforcement Learning", Morgan & Claypool. 2010 `https://sites.ualberta.ca/~szepesva/RLBook.html`

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    `https://sites.ualberta.ca/~szepesva/RLBook.html`
- imitation learning
  - ➡ Attia and Dayan, "Global overview of Imitation Learning", 2018
    `https://arxiv.org/abs/1801.06503`
  - ➡ Daumé III, "A Course in Machine Learning", Chapter 18
    `http://www.ciml.info/dl/v0_99/ciml-v0_99-ch18.pdf`
  - ➡ Osa et al. "An Algorithmic Perspective on Imitation Learning", only intro, 201?
    `https://takaosa.github.io/paper/TFRo_summary.pdf`

Literature

- some good tutorials:
  - ➡ Hal Daumé III, "From Structured Prediction to Inverse Reinforcement Learning", ACL'05
    `users.umiacs.umd.edu/~hal/SPIRL/10-07-acl-spirl.pdf`
  - ➡ Hal Daumé III and John Langford, "Learning to Search for Joint Prediction", ICML/NAACL'16
    `http://hunch.net/~l2s`
  - ➡ Yisong Yue and Hoang M. Le "Imitation Learning", ICML'18
    `sites.google.com/view/icml2018-imitation-learning`
  - ➡ Johannes Heidecke, "Inverse Reinforcement Learning", 2018
    `thinkingwires.com/posts/2018-02-13-irl-tutorial-1.html`

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  - ➡ Johannes Heidecke, "Inverse Reinforcement Learning", 2018
    `thinkingwires.com/posts/2018-02-13-irl-tutorial-1.html`
- neural networks
  - ➡ MT: Graham Neubig, "Neural Machine Translation and Sequence-to-Sequence Models: A Tutorial", 2017
    `https://arxiv.org/abs/1703.01619`
  - ➡ NLP: Yoav Goldberg, "A Primer on Neural Network Models for Natural Language Processing", 2015
    `https://arxiv.org/abs/1510.00726`

What is Imitation Learning?

Definition

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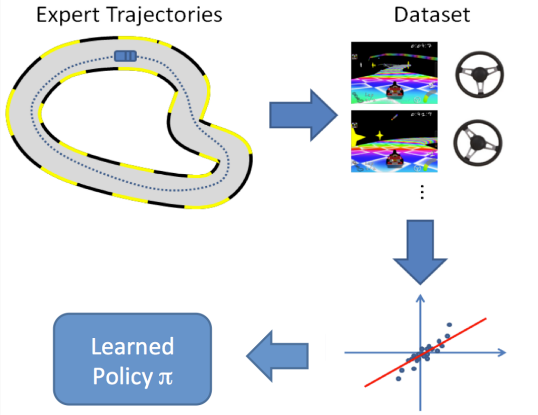
- is it supervised learning?



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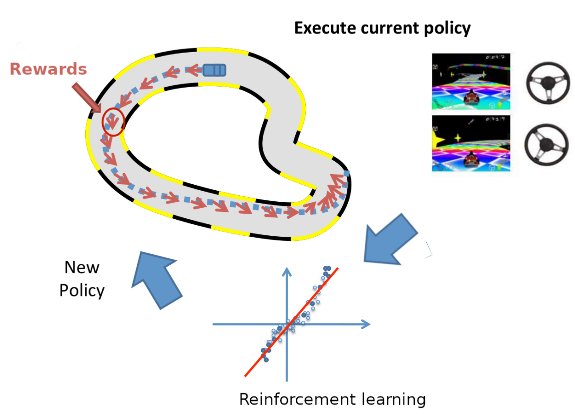
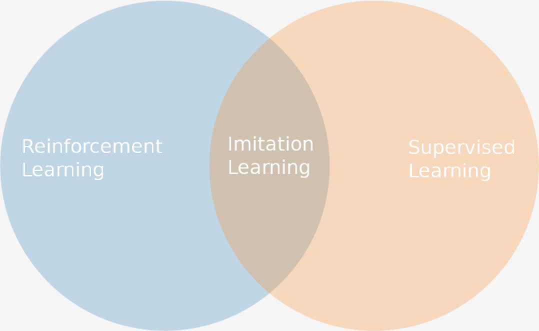


Definition

The purpose of imitation learning is to efficiently learn a desired behavior by imitating an expert's behavior.

Imitation learning is a fusion between supervised learning and reinforcement learning:



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Supervision Strength

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- supervised learning
  (full: explicit goals even for intermediate steps)
- unsupervised learning
  (none: no goals, no rewards)

Supervision Strength

In the order of goal specification:

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  (weak: no explicit goals, but intermediate rewards)
- **imitation learning**
  (stronger: no explicit goals, but some examples how to reach them)
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In the view of different supervision, it makes sense to develop dedicated methods

Applications of Imitation Learning

Applications

- reinforcement learning – impressive but relatively few successes in unrestricted environments
  - ➡ board/computer games, robotics
  - ➡ except: bandit learning really shines e.g. in ad placement, recommendation
- supervised learning – overwhelming majority of all successes of machine learning
  - ➡ vision, music, NLP, ...
  - ➡ all kinds of predictive data analysis
- unsupervised learning – there is progress, but it has yet to catch up

Applications

- reinforcement learning – impressive but relatively few successes in unrestricted environments
  - ➡ board/computer games, robotics
  - ➡ except: bandit learning really shines e.g. in ad placement, recommendation
- **imitation learning** – borrow concepts from reinforcement learning while not throwing away supervised learning
  - ➡ also games (many RL successes are due to imitation learning components)
  - ➡ navigation
  - ➡ self-driving cars
- supervised learning – overwhelming majority of all successes of machine learning
  - ➡ vision, music, NLP, ...
  - ➡ all kinds of predictive data analysis
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Successful applications

- self-driving vehicles
- games and bots
- website optimization
- structured prediction and **NLP**

ALVINN 1988

Super Tux 2009

Mario Bros 2009

Lip movement transfer 2018

Drone obstacle avoiding

Why Imitation Learning?

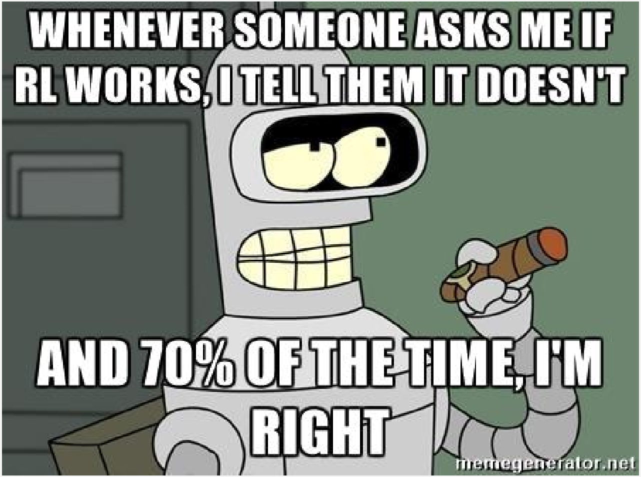
Several ways to argue why we need IL:

- supervision strength
- avoiding some of hurdles in reinforcement learning
- relaxing assumptions of supervised learning
- sample and time efficiency
- deployment safety

Problems with Reinforcement Learning

Why not just use RL?

Why not just use RL?


WHENEVER SOMEONE ASKS ME IF RL WORKS, I TELL THEM IT DOESN'T
AND 70% OF THE TIME, I'M RIGHT
memegenerator.net

[Irpan'18]

Why not just use RL?

[Ng&Russel'00]

[T]he entire field of reinforcement learning is founded on the presupposition that the reward function,. . . is the most succinct, robust, and transferable definition of the task.

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- reward specification, which is often hard to specify exactly
  - ➡ unless we set the rules of the environment (games!)
- even good reward functions can be gamed
- RL is often sample inefficient
- reproducability
- often cannot allow unrestricted exploration

Example: Misspecification of RL rewards

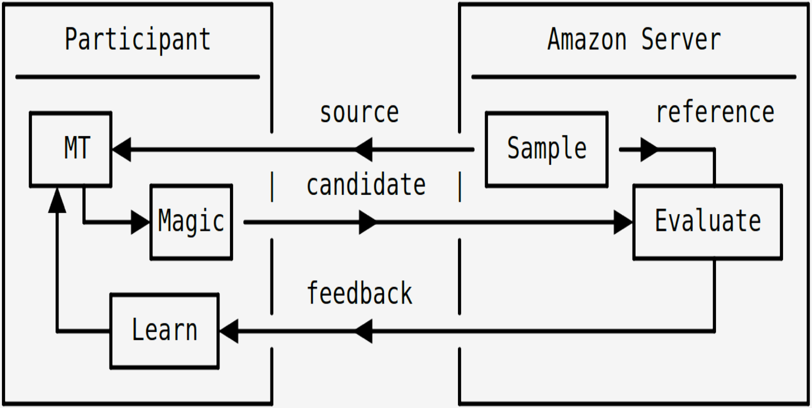
- goal: finish the race
- rewards given also for collecting powerups to the race faster
- farming the powerups gives more points than finishing the race!

[Irpan'18]

Example: Gaming good RL rewards

Amazon/HDU bandit MT learning competition:

- task: adapt to a new domain only using BLEU scores on own translations
- reward: BLEU (sentence level)
- evaluation: BLEU (corpus level)



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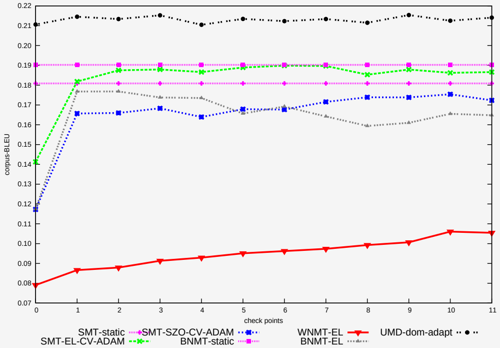

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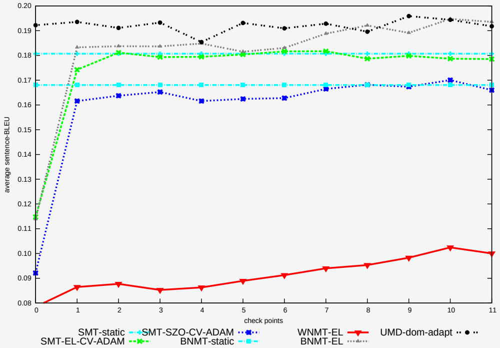


Example: Good rewards can be gamed

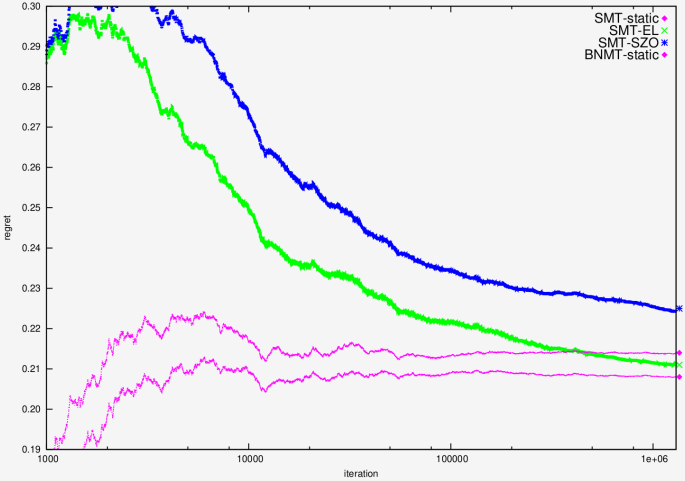
Abstractive summarization with the ROUGE score as reward

[Paulus, 2017]

Button was denied his 100th race for McLaren after an ERS prevented him from making it to the start-line. It capped a miserable weekend for the Briton. Button has out-qualified. Finished ahead of Nico Rosberg at Bahrain. Lewis Hamilton has. In 11 races. . The race. To lead 2,000 laps. . In. . . And.

Example: RL is sample-inefficient

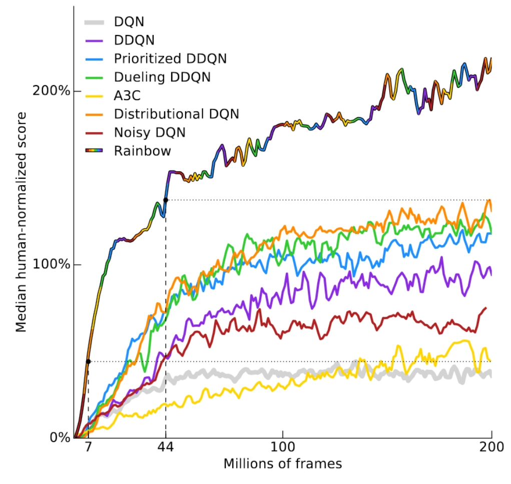
- Amazon/HDU bandit MT learning competition:



- 1M sentences to learn how to translate in a new domain
- humans would learn it from few dozens of examples

Example: RL is sample-inefficient

- Atari games



- 83 hours of play for RL
- humans learn it in minutes

Value Alignment Problem

[Weiner'60]

If we use, to achieve our purposes, a mechanical agency with whose operation we cannot efficiently interfere once we have started it, because the action is so fast and irrevocable that we have not the data to intervene before the action is complete, then we had better be quite sure that the purpose put into the machine is the purpose which we really desire...

Value Alignment Problem

[Samuel'60]

A machine is not a genie, it does not work by magic, [...]The "intentions" which the machine seems to manifest are the intentions of the human programmer, as specified in advance, ...To believe otherwise is either to believe in magic [...]

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An apparent exception to these conclusions might be claimed for projected machines of the so-called "neural net" type [...] Since the internal connections would be unknown, the precise behavior of the nets would be unpredictable and, therefore, potentially dangerous.

Reproducability of RL

[Andreas'17]

Deep RL is popular because it's the only area in ML where it's socially acceptable to train on the test set.

- exaggeration, but partially true
- raises related concerns for conventional supervised learning

Problems with Supervised Learning

Why not just use SL?

By conventional ML we mean supervised batch-learning

- relies on the hard-to-guarantee i.i.d. assumptions
- when used blindly on non-i.i.d data can go wrong
- slow inference for structured SL
- uncertainty guarantees

i.i.d assumption

Convenient paradigm, but

- training data often will not contain important cases
- big data: no-one checks the validity of i.i.d
- in multi-step decision processes the data distribution is dependent on the agent

Example: non-i.i.d and missing data

Example: non-i.i.d and missing data

i.i.d assumption

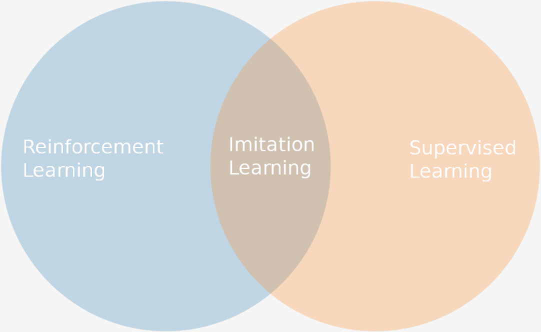
Convenient paradigm, but despite it’s invalidness:

- supervised learning is often works for IL!
- is very simple
- always should be tried first

What does Imitation Learning add?

Recall

Imitation learning is a fusion between supervised learning and reinforcement learning:



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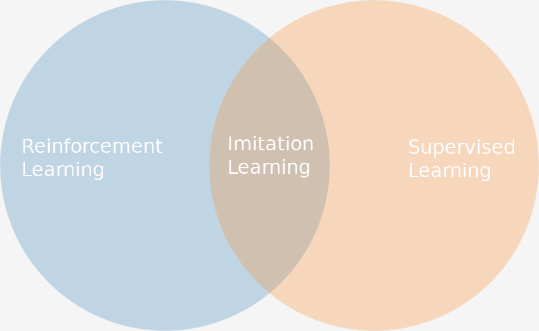

Question: Given this relation what could be said about ways to solve IL?

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- learning hidden objectives of the expert's behavior – 'inverse RL' (reduction to RL)

Imitation Learning

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Can be achieved via:

- directly replicating the expert's behavior – 'behavioral cloning' (reduction to SP)
- learning hidden objectives of the expert's behavior – 'inverse RL' (reduction to RL)
- letting teacher interfere to correct bad behaviour – 'data aggregation' (better reduction to SP+online learning)
- observing teacher solving an unfinished task – 'policy aggregation' (better reduction to SP+online learning)

Key differences to RL

- not using rewards (at least not relying on them directly)
- use of examples or querying an interactive teacher

Key differences to conventional ML

- structural constraints
- distribution shift
- cost of gathering examples

Afternoon lecture

- presentation
- projects