Imitating Human Play from Game Logs (Workshop)

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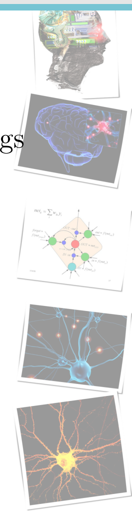
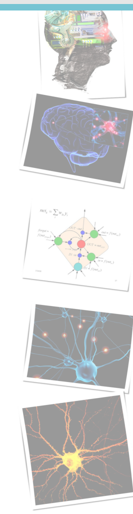


Imitating Human Play: A brief introduction

The workshop



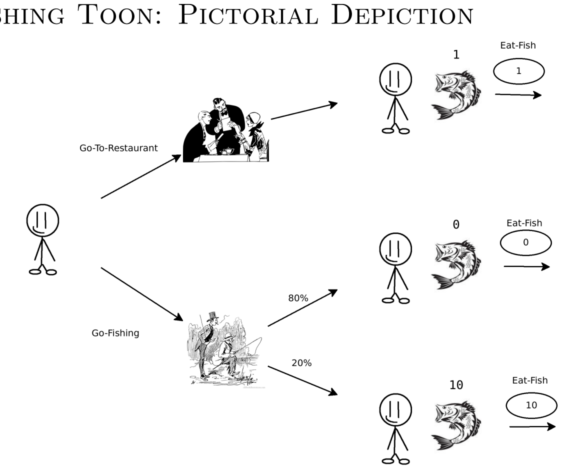
Goals

- Be able to explore the relevant literature independently.
- Gain enough experience in supervised learning methods in order to incorporate player behaviours in your game.
- What you will need:
  - A Laptop, almost everything tested in Mac/Linux, NOT windows
  - A working python installation
  - Clone this repo: **https://github.com/aigamedev/nuclai15**
  - Make sure you can run train.py (i.e. see which imports are failing and get them with pip)
  - Most important imports: **pandas, scikit-learn, scikit-neuralnetwork**

The problem

- Let's assume you have access to real game logs, i.e. data generated through human game-plays
- Is it possible to replicate, even partially, the observed behaviour of players?
- Why would anyone want to do that?
  - Copy player behaviour and incorporate into NPCs (i.e., more "human-like choices").
  - Find optimal counter-strategies and incorporate into NPCs.
  - Bootstrap some other learning method.

Fishing Toon: Pictorial Depiction



Expected Reward

- In a sim like-game a player has to choose between two different actions
- `Go-To-Restaurant` or `Go-Fishing`

The Markov Decision Process

- The primary abstraction we are going to work with is the Markov Decision Process (MDP)
- Very rarely made explicit, though always there implicitly
- MDPs capture the dynamics of a mini-world/universe/environment/game
- An MDP is defined as a tuple $< S, A, T, R, \gamma >$ where:
  - S, $s \in S$ is a set of states
  - A, $a \in A$ is a set of actions
  - $R : S \times A$, $R(s, a)$ is a function that maps state-actions to rewards
  - $T : S \times S \times A$, with $T(s'|s, a)$ being the probability of an agent landing from state s to state s' after taking a
  - γ is a discount factor - the impact of time on rewards

Goals (a bit more formally)

- Learn $\pi(s, a)$, a mapping between states and actions, called the *policy*
- Intuitively: "How should I act under this and this condition"?
- If we have logs from past games we can try to learn this mapping
- We have just restated our goal in more formal fashion - let's discuss a bit more

Real games

- Real games often have a very large action and state spaces
- We can keep track of what players are doing
- . . . but even for the simplest of cases learning a direct mapping is impossible
- Hence, the need to approximate (more on this later. . .)
- We will explore Linear Functions and Neural Networks in this workshop, but **many** more options are available

Inverse Reinforcement Learning

- "Given that a player is acting optimally, can we copy her behaviour?"
- We are not going to cover this here, but it's worth discussing it
- Why does it even make sense?
  - Is it more concise to learn $R*$ compared with π?
  - Need for assumptions over the possible class of policies

Behavioural/Supervised learning

- Learn the sequences of actions using supervised learning
- Much simpler approach
- Obviously you have observed some sequence of $(s_0, a_1 ... s_n, a_n)$
- Learn a policy π from these actions directly
- This is what we are going to discuss in this workshop

Preference Learning

- Supervised Learning
- One can learn to rank actions
- Is action a_0 better than action a_1 under state s?
- Multiple methods of doing this, not to be covered here

Reinforcement Learning

- Not covered
  - ... but you can possibly treat action sequences as some kind of if implicit policy
  - ... and try to learn a value function
    - "What is the the average sum of expected rewards at state x?"
- With off-policy learning you might event attempt to learn a better policy than the one actually being executed!
  - Search Q-Learning for more

The workshop

- Clone this repo: **https://github.com/aigamedev/nuclai15**
- Run train.py
- Make sure you you can run everything
- We now essentially have a supervised learning problem

The Data pipeline

- Define the problem
- Data collection
- Data munging
- Metric selection
- Algorithm selection
- **Post-processing** (not covered)
- **Deployment** (not covered)
- **Experimental Evaluation** (not covered)
- (Above according to Microsoft research)

Problem definition

- Everything we discussed until now
- ...find what the agent is going to go next
- Define 3 actions per axis
- Concentrate ONLY on movement, i.e. where am I going to move next?
  - Re-create the Markov Property using 10 past (x,y) observations
  - Use other player positions
  - Let's see some code

Data collection

- You will need some kind of in-game probe
- Sensors on a player
- Logs from some source
- For DOTA there are online matches

Data Munging (1)

- Key tools: Pandas, numpy, scipy
- Create CSV for further pre-processing
- extract_data_vectors.py
- You can run it, but it requires a game log .dem file

Metric Selection - Algorithm selection

- Inside train.py
- Let's have a look
- Mean Squared Error is our selected metric - but it's not the optimal

From Linear Regressors to Neural Networks

- Regressor in the form $y_w(\theta) = w_0\theta_0 + w_1\theta_1 + ... + w_k\theta_k + b$
  - Equivalently $y_w(\theta) = \boldsymbol{w\theta} + \boldsymbol{b}$
  - Learn $\boldsymbol{w}$
- Nested $y_w(\theta) = \boldsymbol{w^n}(max(0, \boldsymbol{w^{n-1}}(max(0, ...) + \boldsymbol{b^{n-1}})) + \boldsymbol{b^n}$
  - Learn $\boldsymbol{w}$

Modern tricks of the trade

- Better initialisation methods (e.g., unsupervisded pre-training, Glorot initialisation)
- Better training methods (e.g., ADAM, RMSPROP)
- Better activation functions/units (e.g., Rectifiers, Maxout)
- Better regularisation methods (e.g., Dropout)
- Better weight sharing/convolutional layers (e.g., Fractional Max-pooling)
- Better hardware (GPUs)
- **Most of these have equivalents in sklearn-neuralnetwork**

Workshop Tasks

- Run experiments using a dummy classifier
- Run experiments using a Linear Classifier
- Run experiments using a Neural network
- Change the metric to "accuracy score"
- Each run should get you progressively better results
- Move some of the pre-processing to a different CSV file and load this (e.g., past examples)
- Change network architecture (e.g., number of neurons) and re-run the experiments
- Change train.py to save the classifier to a file (using python pickle)