A Deep Reinforcement Learning Framework for Financial Portfolio Management

AI Research

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Introduction to Portfolio Management

Portfolio Management

Portfolio Management is the selection and overseeing of a group of investments that meet the financial objectives of the investor e.g. Hedge Funds, Pension Funds, Governments, Institutions etc.

Investors typically seek to maximise returns for a given level of risk, also know as the Markowitz efficient frontier. [1]

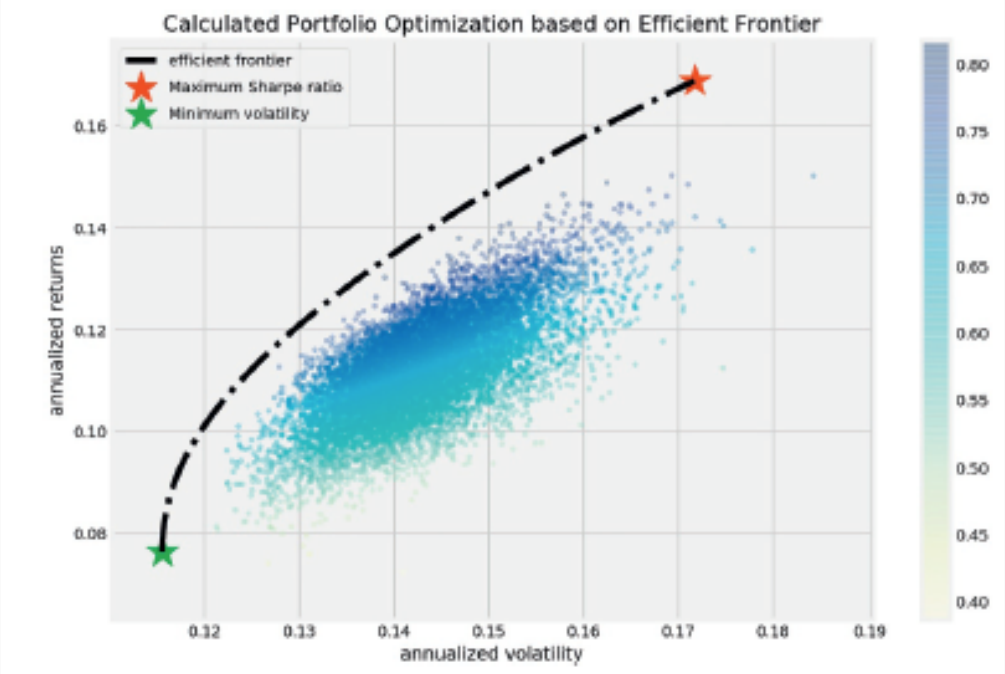


Figure 1: Demonstration of Efficient Frontier [2]

Advances in Portfolio Management

Baseline Investment priorities

- Strong return on investments
- Optimised for risk appetite
- Tailored to hedge downside risk

Additional modern day investment priorities

- Environmental concerns of business e.g. climate change, sustainability
- Social effects of business e.g. diversity, human rights, consumer protection, animal welfare
- Corporate Governance e.g. management structure, employee compensation, executive compensation.
- AI can unlock additional returns and remove emotional human decision making

This has lead to the rise of ESG (Environmental, Social, & Corporate Governance) data, and AI for electronic trading.

Introduction to Reinforcement Learning

Reinforcement Learning

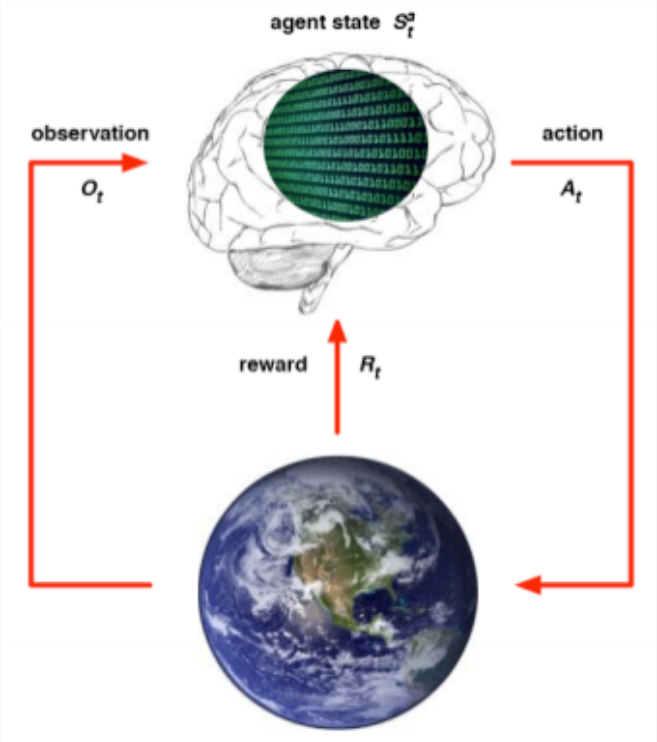
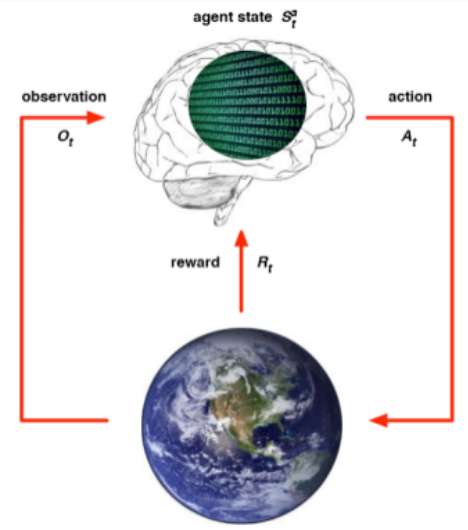


Figure 2: Reinforcement Learning Decision Space. Source-David Silver (UCL/DeepMind) [3]

Reinforcement Learning



Formally,

- O_t: Observation
- A_t: Action
- R_t: Reward
- H_t: History
  $H_t = O_t, R_t, A_{t-1}, O_{t-1}, R_{t-1}, ..., O_1, R_1, A_1$
- S_t: State
  $S_t = f(H_t) = f(O_t, R_t, A_{t-1}, ..., O_1, R_1, A_1)$

Reinforcement Learning Example

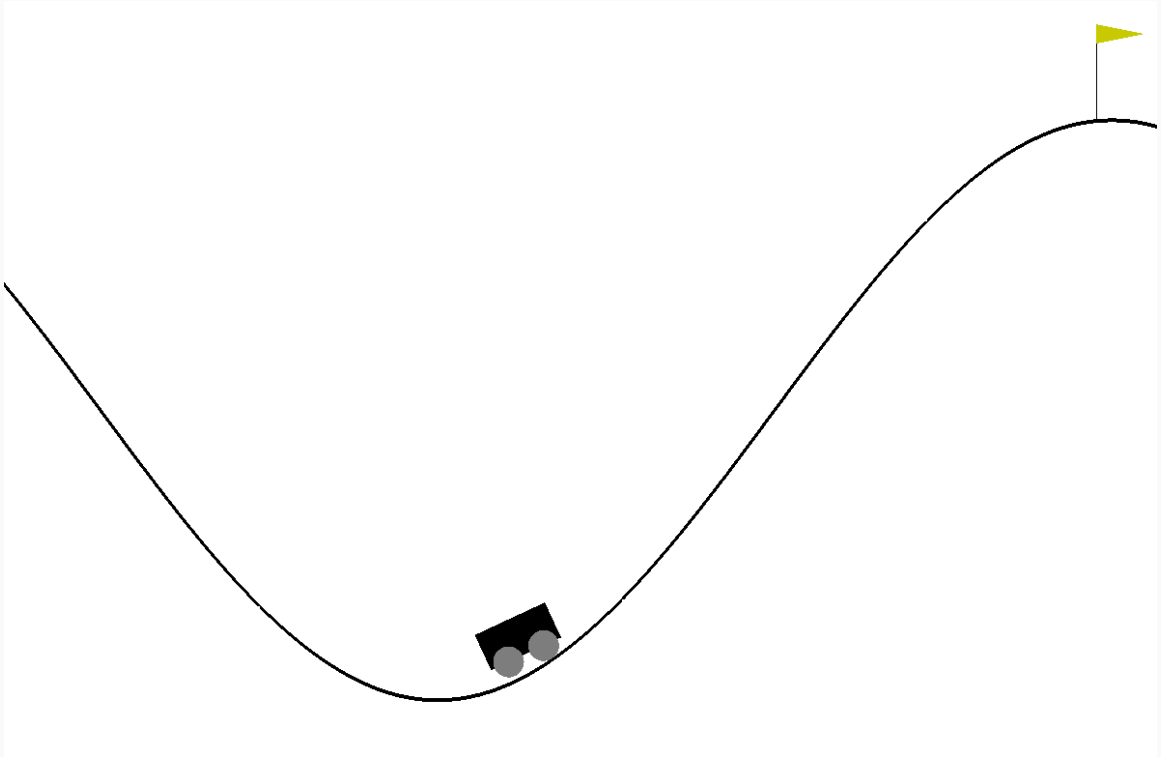
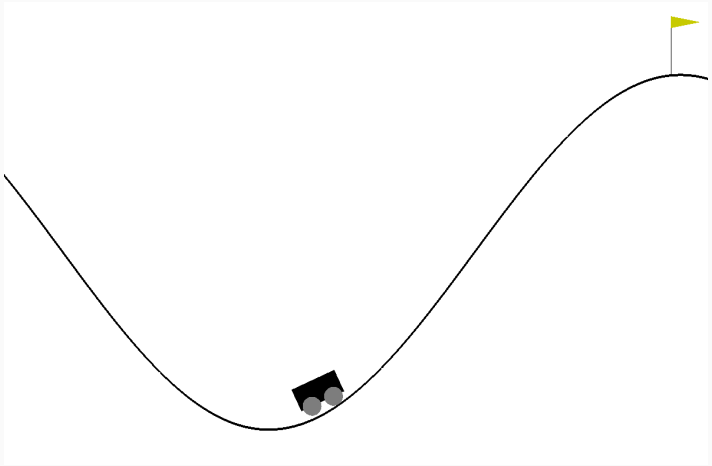


Figure 3: Classic example task for reinforcement learning, Mountain Car by OpenAI

Reinforcement Learning Example



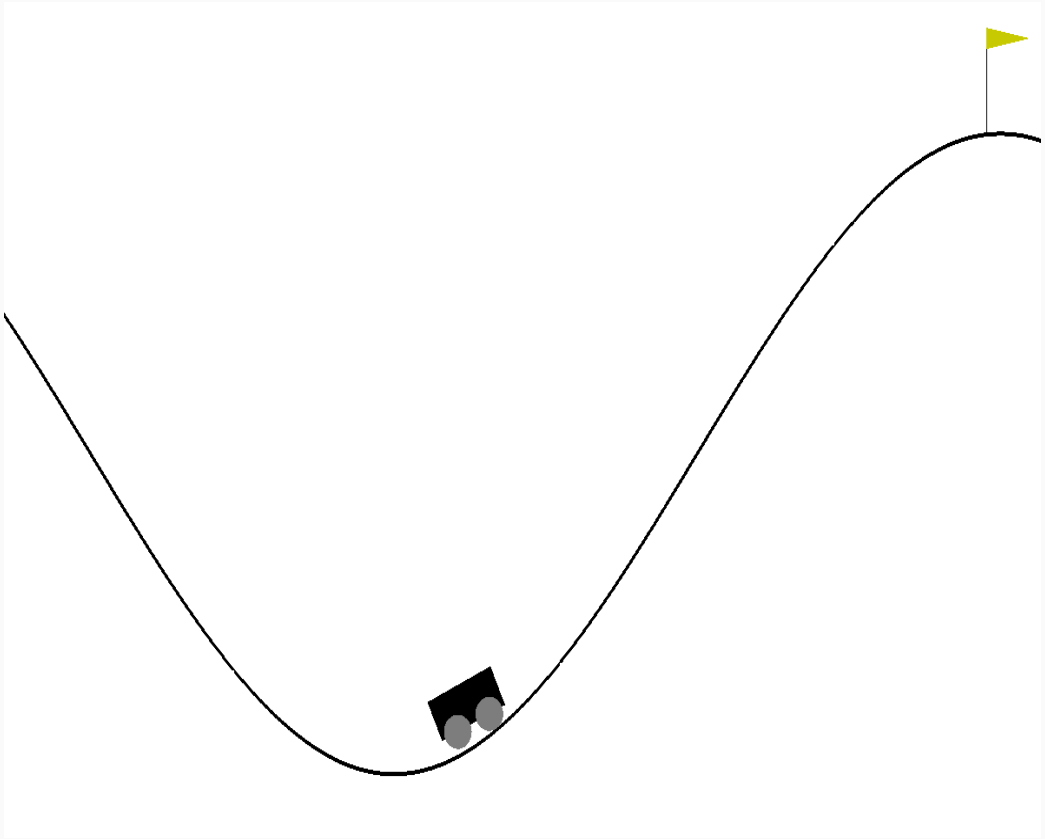
- S_t: $(Position_t, Velocity_t)$
- A_t: $(-1, 0, 1) = (left, none, right)$
- R_t: -1 if not in goal state, else 0.

Can we teach the car to go up the hill?

A logical (rule based) agent may just decide to always go right, good move?

Reinforcement Learning Demonstration

Always go right?



Reinforcement Learning Demonstration

To teach the agent, introduce:

- $Q(S_t, A_t)$: Action Value Function

We use the Bellman Equation to update Q values:

$$Q^{new}(s_t, a_t) = (1-\alpha) \cdot Q(s_t, a_t) + \underbrace{\alpha}_{\text{learning rate}} \cdot (r_t + \overbrace{\gamma}^{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\substack{\text{Q value of optimal} \\ \text{action in next state}}})$$

Reinforcement Learning Demonstration

Reinforcement Learning pseudo algorithm:

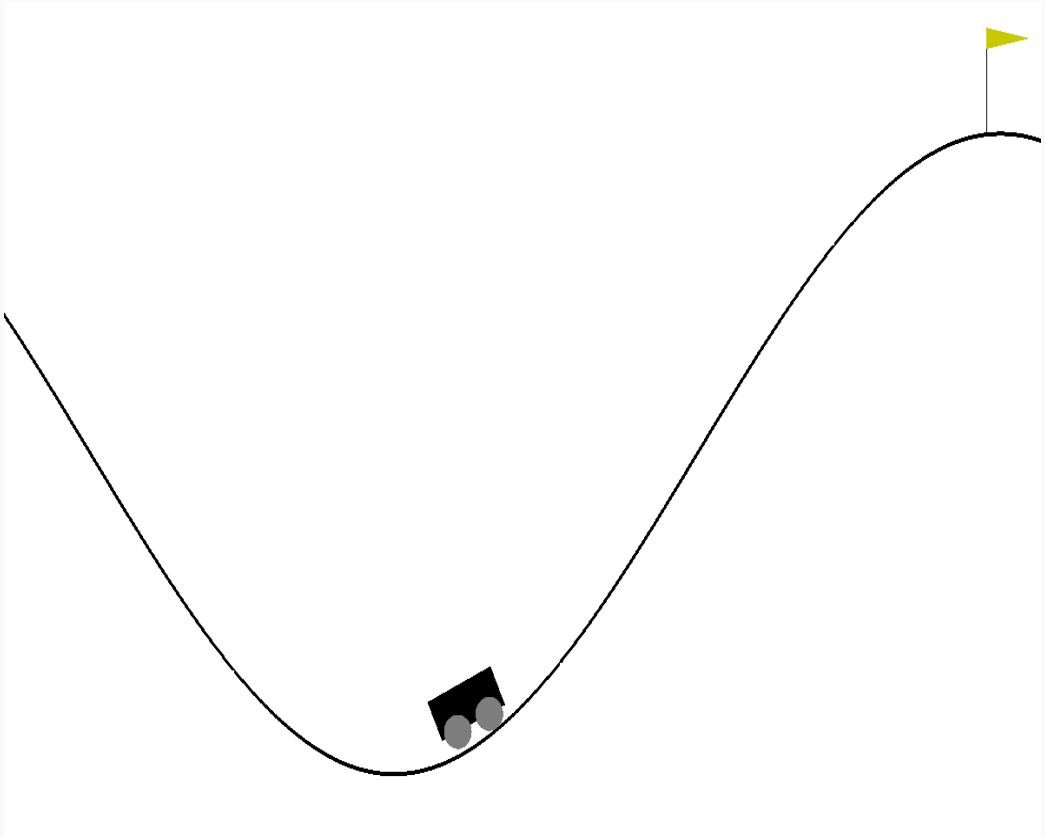
1. Discretise state space. Initialise parameters α, γ
2. Assign Q values uniformly random between 0-1
3. For each episode until goal
   - 3.1 Observe state s_t, make action a_t
   - 3.2 Observe reward r_t, new state s_{t+1}.
   - 3.1 If new state=goal, finished
   - 3.2 Else,
     - Estimate action with highest Q value in new state
     - Update Q table via Bellman eqn.

Which creates a Q table, something like this:

		Velocity		
		-0.07	...	0.07
Position	-1.2	(0,0.1,1.33)	...	(0.4,0.7,3.6)
	...	...	...	...
	0.5	(10,10,10)	...	(10,10,10)

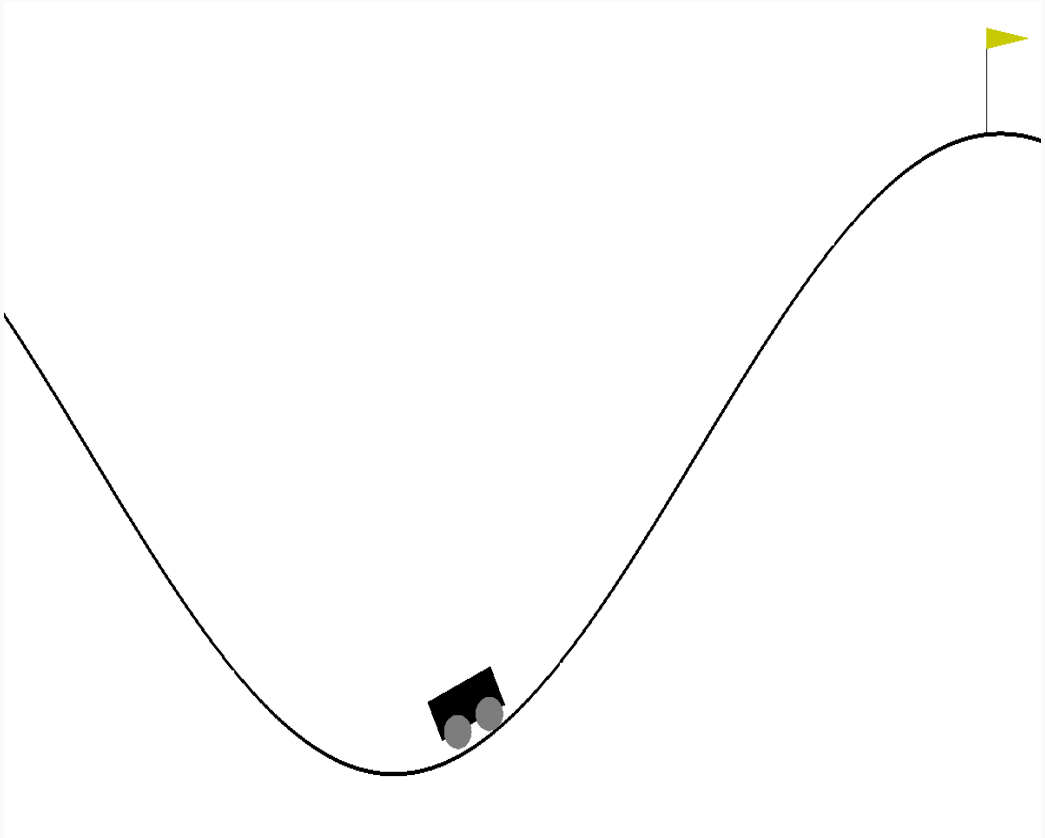
Reinforcement Learning Demonstration

Bellman Q Learning Episode 0



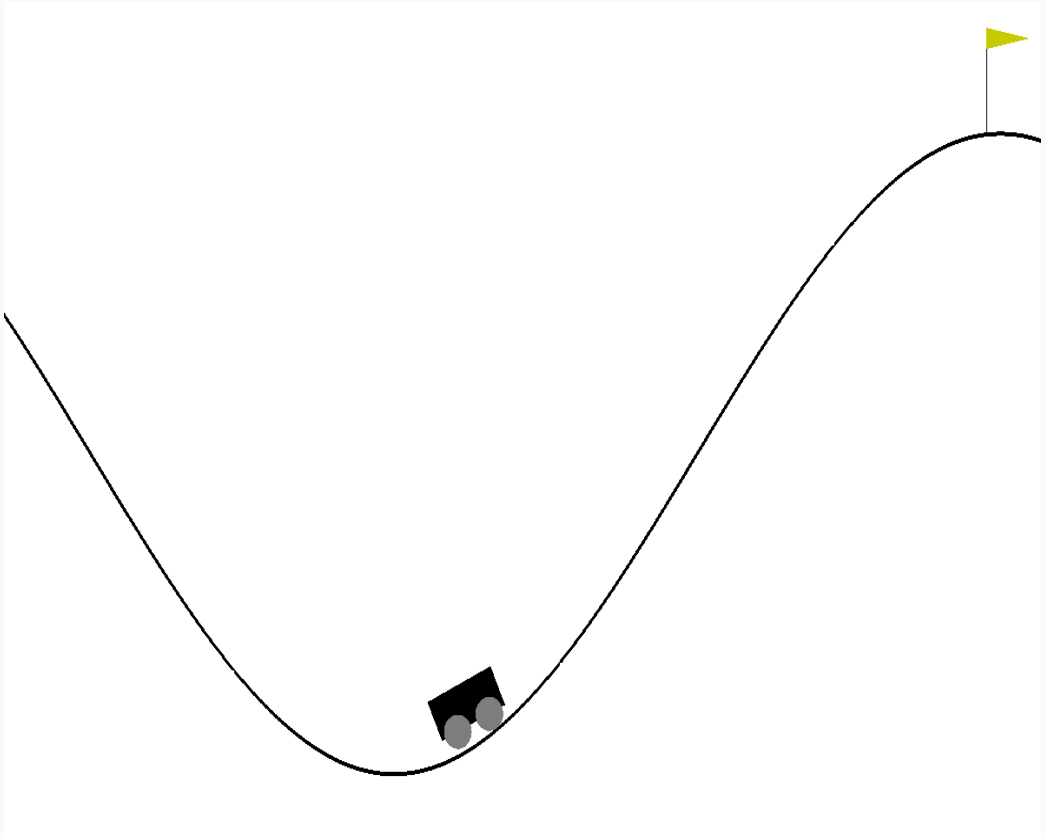
Reinforcement Learning Demonstration

Bellman Q Learning Episode 4000



Reinforcement Learning Demonstration

Bellman Q Learning Episode 12000



Reinforcement Learning Demonstration

Not bad! But some problems:

- A lot of iterations (12000), around 3 minutes to train. Brute force computation.
- Discrete state space - Only have a ”lookup” table for Q values
  - What happens if the hill becomes slightly longer? We’ve no space in the Q value for the unseen points.
- Q table could be terabytes/petabytes of memory for even somewhat difficult games e.g. Atari Pong.

Reinforcement Learning Demonstration

Solution = Deep Q Learning!

- Allows approximation of much larger state spaces than Mountain Climb.
- Helps learn much more complex decision environments e.g. Go.

Method

1. Use a neural network to get Q values based on state, $Q = f(S_t)$. Expanded to continuous state space, so no more table lookup.
2. Update weights in neural network as we learn more about the valuable actions in different states.
3. For each time step, and each state, take actions that maximise Q value.

Reinforcement Learning Example

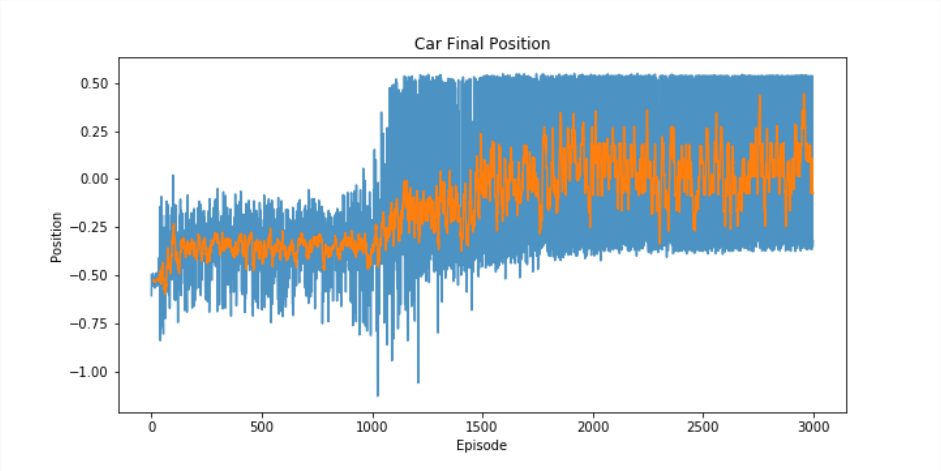


Figure 4: Performance of Deep Q Learning Agent on Mountain Climb

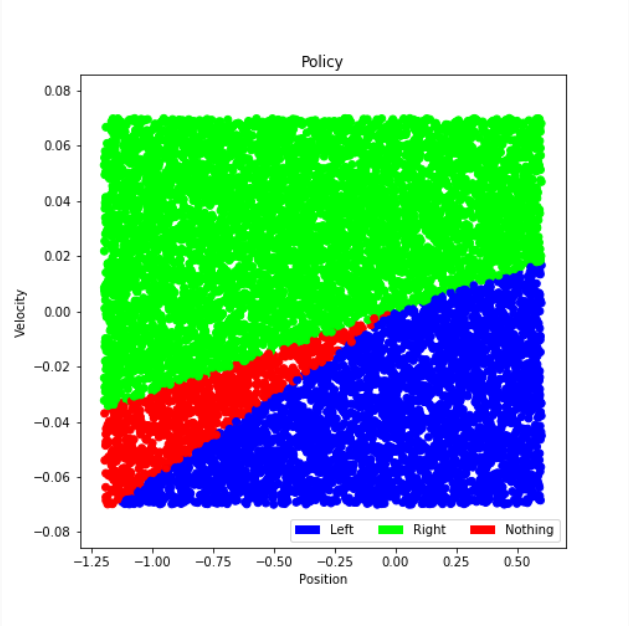


Figure 5: Learned policy function (action function) on Mountain Climb

Project Overview

Paper Overview

A Deep Reinforcement Learning Framework for the Financial Portfolio Management Problem [4]

- Proposed framework based on Ensemble of Identical Independent Evaluators (EIIE) topology.
- EIIE inspects the history of each asset and evaluates it potential growth for the future. The output becomes the new portfolio weights for the coming trading period.
- Uses experience replay to train EIIE to output a set of optimal portfolio weights. Achieved exceptional ten fold returns in 3 different cryptocurrency portfolio testing environments.

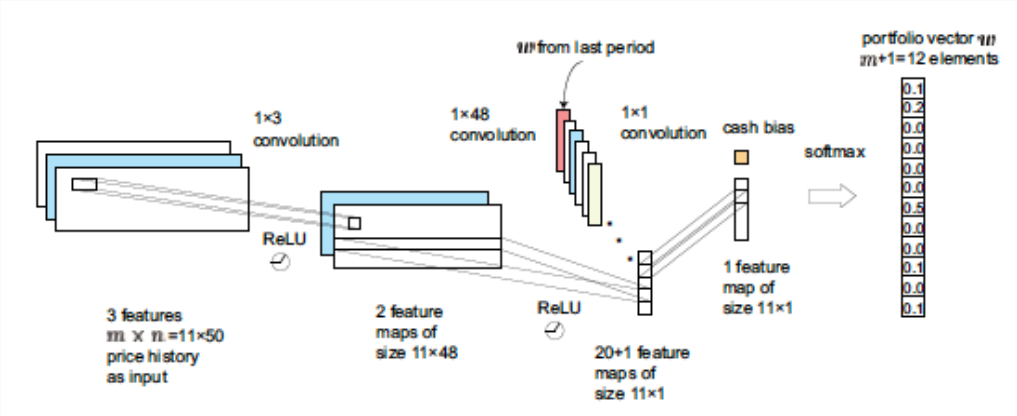


Figure 6: CNN Implementation of EIIE

Literature Overview

- Classical portfolio management techniques include the capital asset Pricing Model (CAPM) and Fame French 3 and 5 factor models. These techniques are however quite rigid formulas and are not the most useful for making automated trading decisions.
- Statistical Arbitrage involves making trading decisions based on the correlation of two or more instruments. Can be long only, or long-short.
- Deep supervised learning research has exploded for price prediction, but there are few successful applications in the literature for price prediction or portfolio management due to non-stationarity of financial time series (although incredibly useful as part of a reinforcement learning agents' makeup).

Refinitiv ESG data

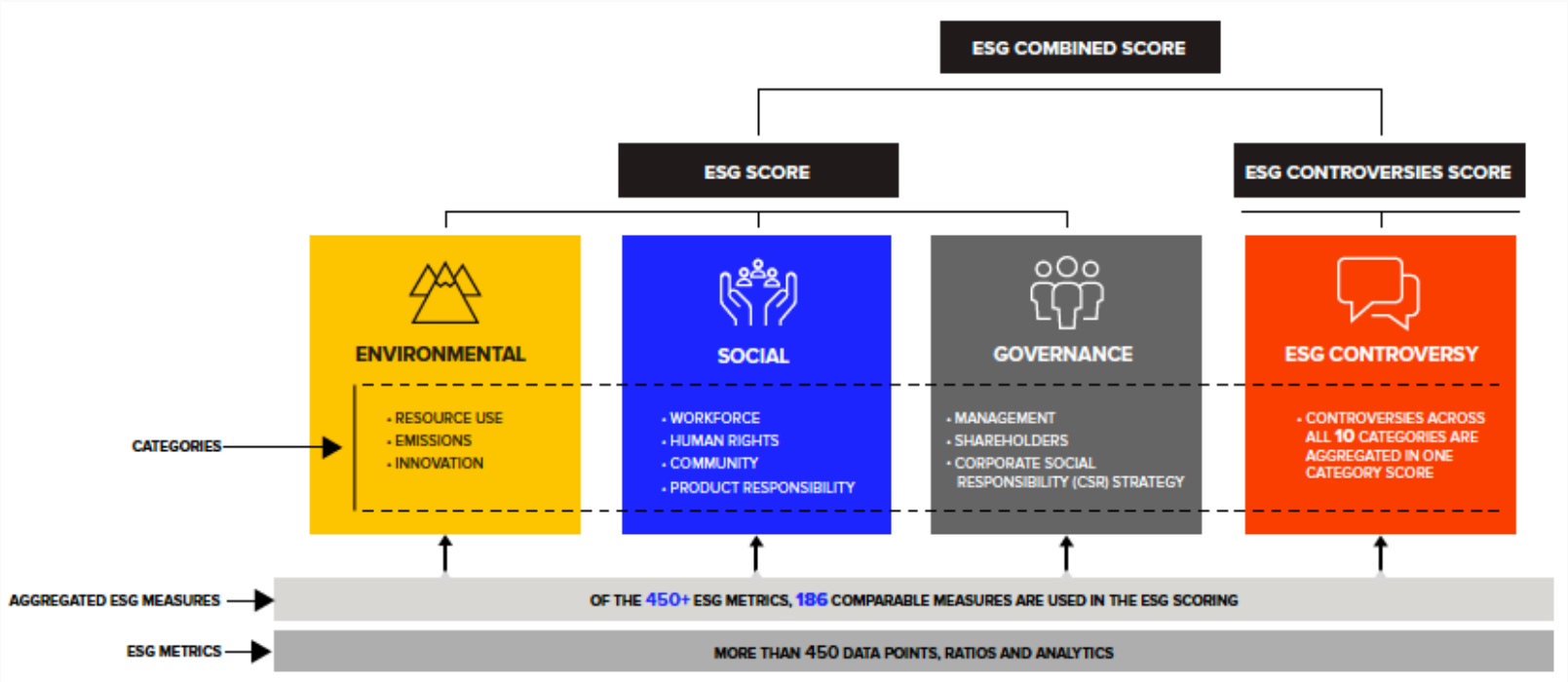


Figure 7: Refinitiv ESG Data Overview

The Data

- Time frame: 28/09/2004 - 28/09/2018
- Number of trading days: 3654
- Frequency: Daily
- Indices: CAC40, DAX, FTSE100, Nikkei 225, S&P500, TSX
- Financial Metrics: Open, High, Low, Close

The Algorithm

1. Portfolio Environment: Easily take batches of data to feed into neural network. Calculate rewards based on returns between time steps.
2. Deep Deterministic Policy Gradient [5]:

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_t, a=\mu(s_t)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s_t}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

3. Backtest: Store Results of Portfolio Returns for each strategy
4. Benchmark Strategies: Tests agents results against well documented trading strategies e.g. ”Follow the winner”, Mean Reversion, Online Newton Step Algorithm, and others.
5. Evaluation: Present cumulative returns of each agent.

The Network Architecture

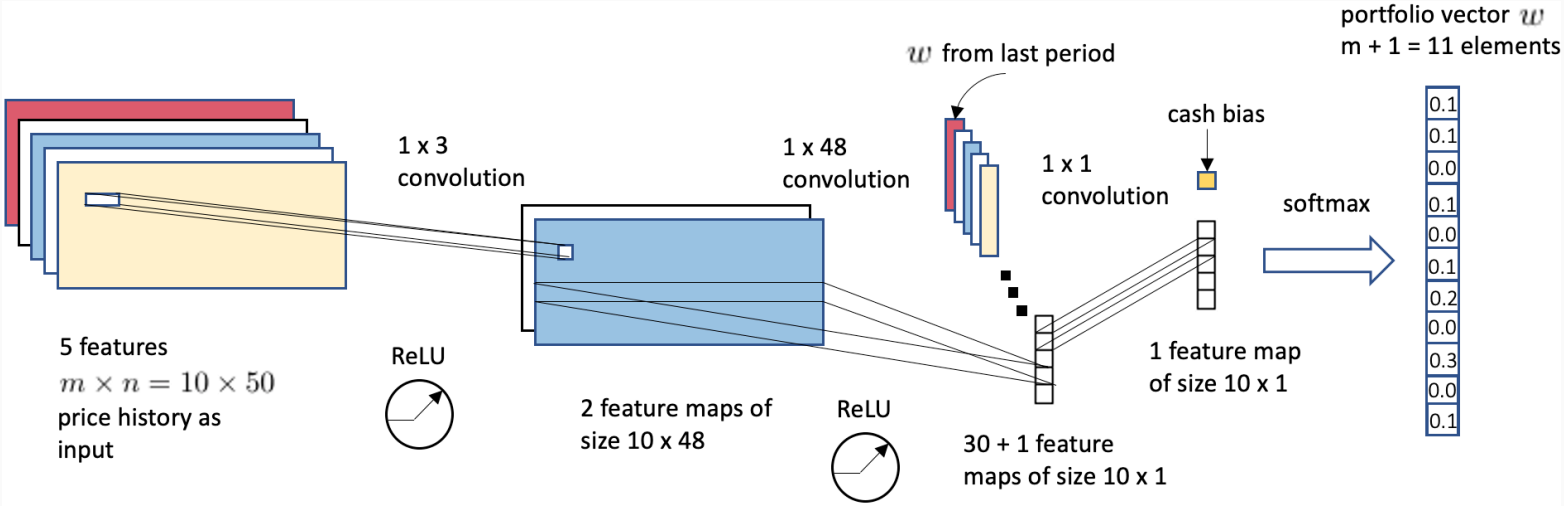


Figure 8: Reinforcment Learning Agent Network Architecture

Results

Results

- Firstly try with purely financial-focused reinforcement learning agent. 16 of 24 agents (66%) were able to beat the benchmark universal portfolio theory agents.
- Next, 43 out of 72 (60%) of financial and sustainability focused agents beat their benchmarks.
- Financial and sustainbility agents performed significantly better overall with regards to financial returns and sustainabillity.

Financial Agent Results

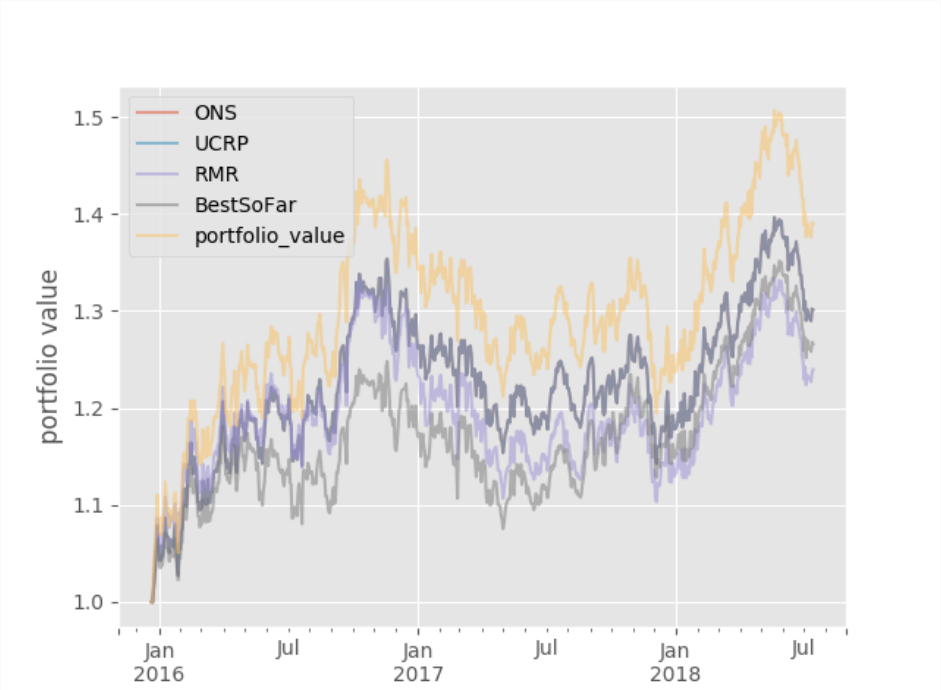


Figure 9: TSX Backtest Plot

data=TSX_3	fAPV	SR	MDD
BestSoFar	1.266	0.523	**0.138**
ONS	1.301	0.564	0.156
RMR	1.240	0.437	0.172
UCRP	1.301	0.564	0.156
$\max(p_T)$	**1.390**	**0.610**	0.180
$\text{avg}(p_T)$	1.263	0.560	0.134
$\text{SD}(p_T)$	0.153	0.033	0.077

Figure 10: TSX Backtest

Financial and Sustainability Agent Results

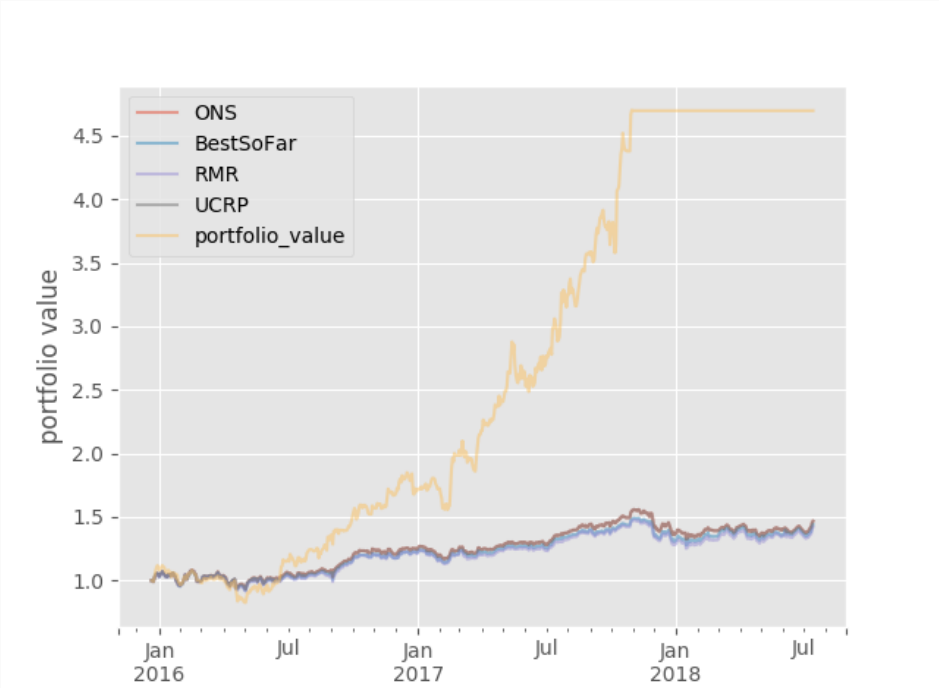


Figure 11: Nikkei Backtest Plot

data=Nikkei 225_{12}	fAPV	SR	MDD
BestSoFar	1.440	0.839	**0.143**
ONS	1.467	0.876	0.151
RMR	1.420	0.791	0.154
UCRP	1.467	0.876	0.151
$\max(p_T)$	**4.696**	**2.034**	0.261
$\text{avg}(p_T)$	2.201	0.973	0.213
$\text{SD}(p_T)$	1.452	0.683	0.048

Figure 12: TSX Backtest

Summary

Current Portfolio Management Trends:

- Data-driven investing is taken over, as it removes emotional trading.
- More focus on ESG investing than ever before, and only set to increase.

Why Deep Reinforcement Learning?

- Non-stationary nature of financial time series has made current supervised learning prediction models unsuccessful.
- Deep Reinforcement Learning enables the agent to learn directly from playing in the simulation environment.
- Fantastic results and better capability to deal with non-stationary financial time series environments.

Summary of Research Questions

New Research Questions:

- How does our strategy compare against other off the shelf algorithmic trading strategies? Better than all on average.
- What is the environmental impact of current algorithmic trading strategies? Better than all on average.
- Can we beat the benchmark strategies more often than not? Yes, and significantly higher returns in out-of-sample backtesting.

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Q&A