

Deep RL for algorithmic trading, Eric Benhamou

Executive summary

- Deep Reinforcement Learning (DRL) applications to finance are still unknown, whereas it is the technique of choice in games and has reached spectacular levels of efficiency, robust in non stationary environments.
- ► In this work, we apply deep policy gradient methods to optimal trading decision.
- We show this leads to acceptable results and provide a model free alternative to rule based trading algorithms.

Motivating Questions	Experiment	Train
 Can an artificial agent learn to trade successfully? [Yes] Can data non-stationarity be 	 Done on Facebook stock Train: 01June2012 to 31May2018 (1,509 days = 87.7%) 	Agent RL Long Naive

- solved? [Yes]
- Can we do with a few thousands points? [Yes]
- If markets change, can the agent act appropriately? [Yes]
- Test: 01June2018 to 04Apr2019
 (212 days = 12.3%)
- Train mostly bullish
- Test quite different from train
- Impact of learning rate



Key concepts

- Problem solved using A3C method as in [4] and [3]
- Non Markovianity handled by large buffer (20 days)
- Q function: 2 × 256 ELU + softmax activation
- Reward with Sharpe ratio for better risk balance than [1] or [2]
- Iteration though deep policy gradient method faster than [5]

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Test



Model	Results	References
	Deep PGM (Reward=Sharpe)	Yue Deng et al. "Deep Direct Reinforcement Learning for Financial Signal Representation and



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