A framework for deep reinforcement learning in a FOREX trading context

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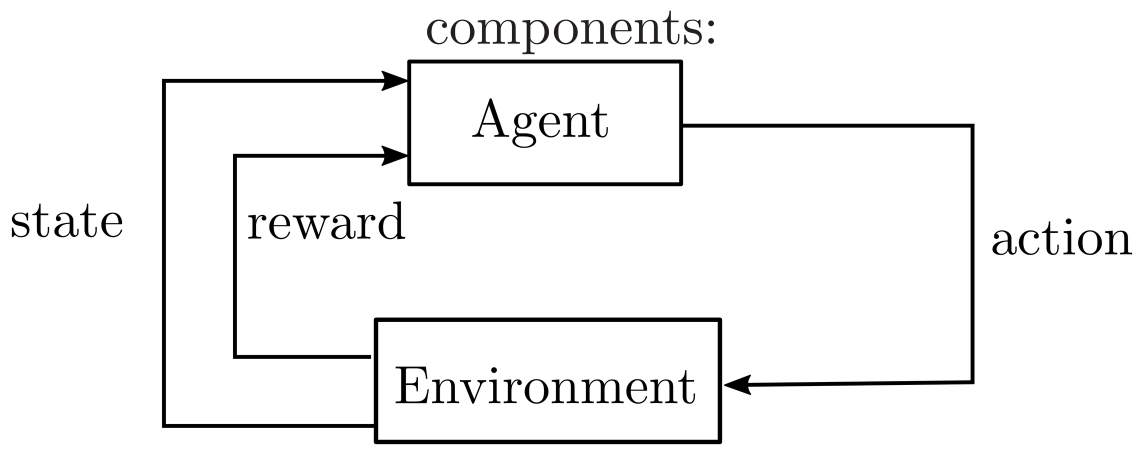
1. Introduction

The term *financial market* refers broadly to any marketplace in which the trading of securities occurs. Such a market is classified according to the types of securities traded. The Forex market is a global over-the-counter market for trading one currency in exchange for another. It was estimated that the Forex market experienced a daily trading volume of $6.6 trillion during the last quarter of 2021, making it the largest financial market in the world. *Finance theory* describes market efficiency in terms of two fundamental notions: Efficiency of information and efficiency of operation. Being efficient with information is expected to lead to an increase in profitability as well as a decrease in inherent loss. Human traders are, however, riddled with inefficiencies and this gave rise to the notion of trading algorithms during the 1970s. Trading algorithms execute trades without the inefficiencies apparent in human traders, as well as, with an increase in efficiency of information and operation, thus it is expected from trading algorithms to outperform human traders. According to the literature, the implementation of machine learning algorithms in trading has achieved some notable results [1], where paradigms of machine learning include supervised learning, unsupervised learning, and reinforcement learning. We present a *deep reinforcement learning* framework in this poster which, if implemented correctly, is capable of minimising the inefficiencies of human traders, thereby leading to greater potential returns.

2. Reinforcement learning

Reinforcement learning involves adopting a trial-and-error approach in conjunction with a reward system to learn some perform some task in a created environment. This type of learning consists of four primary components: An agent (representing a decision maker or learner), actions taken (what the agent can do), the reward received based on actions actions and, the environment (everything the agent interacts with) [2]. In the event of discovering a desirable solution, the solution is reinforced by supplying a reward to the agent. In the event of an unfavorable outcome, on the other hand, the agent is implicitly forced to reiterate by being awarded a penalty until a suitable solution is found.

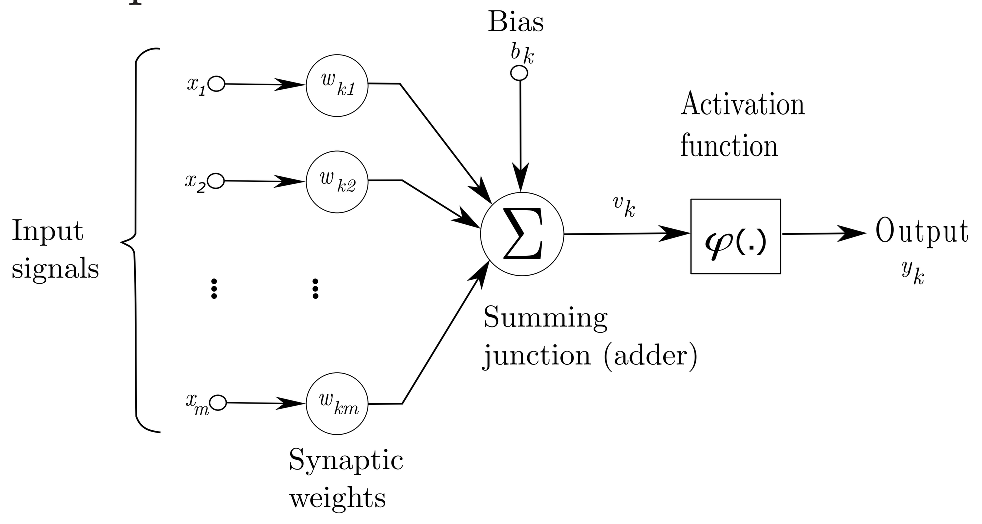
Graphical illustration of reinforcement learning components:



3. Deep reinforcement learning

Neural networks (NN), are excellent function approximators, which are particularly useful in reinforcement learning problems when the state space or action space is too large to enumerate. Reinforcement learning algorithms in combination with NNs are capable of solving highly complex problems as is the case in an algorithmic trading environment.

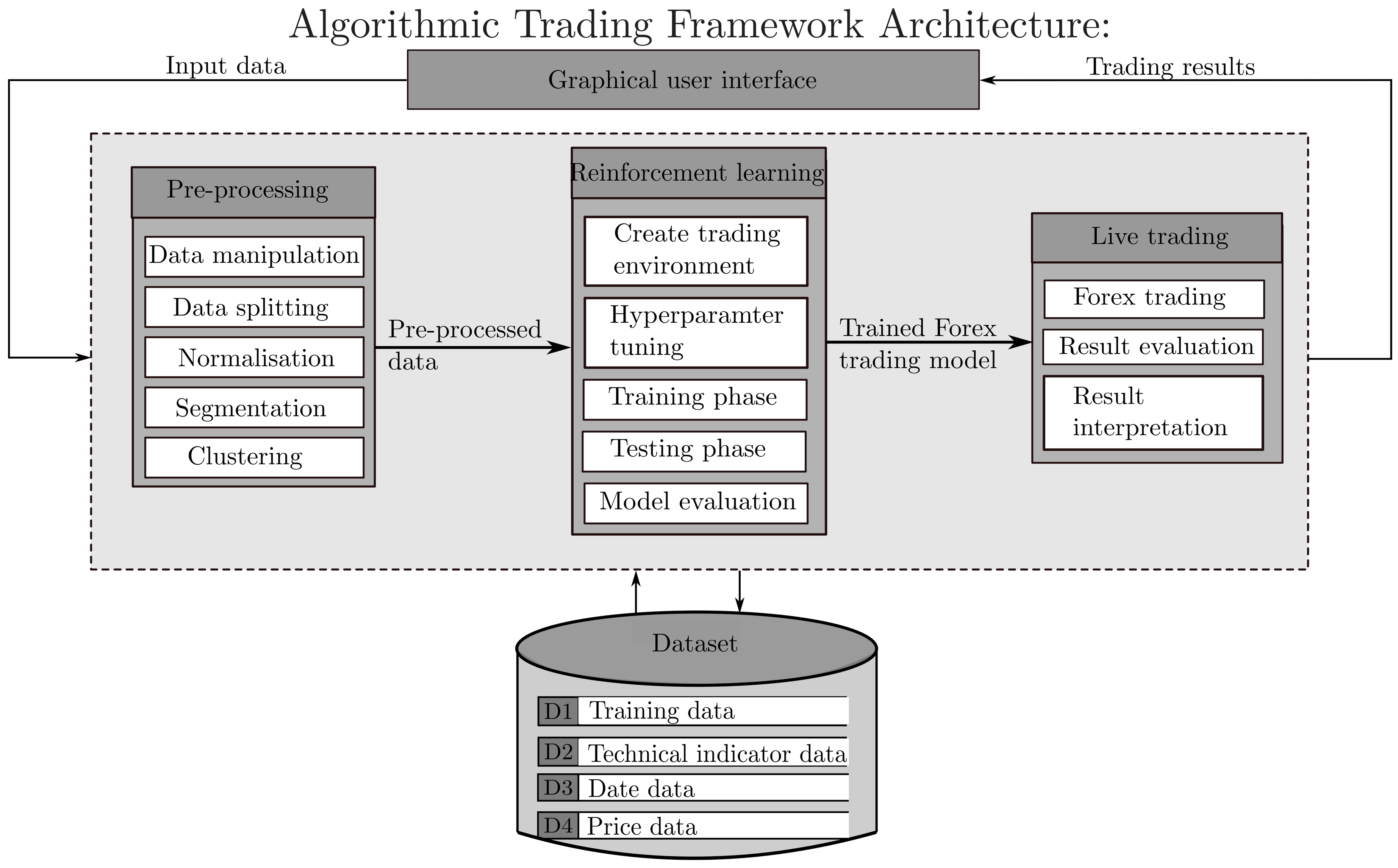
Graphical illustration of a NN neuron:



4. Framework

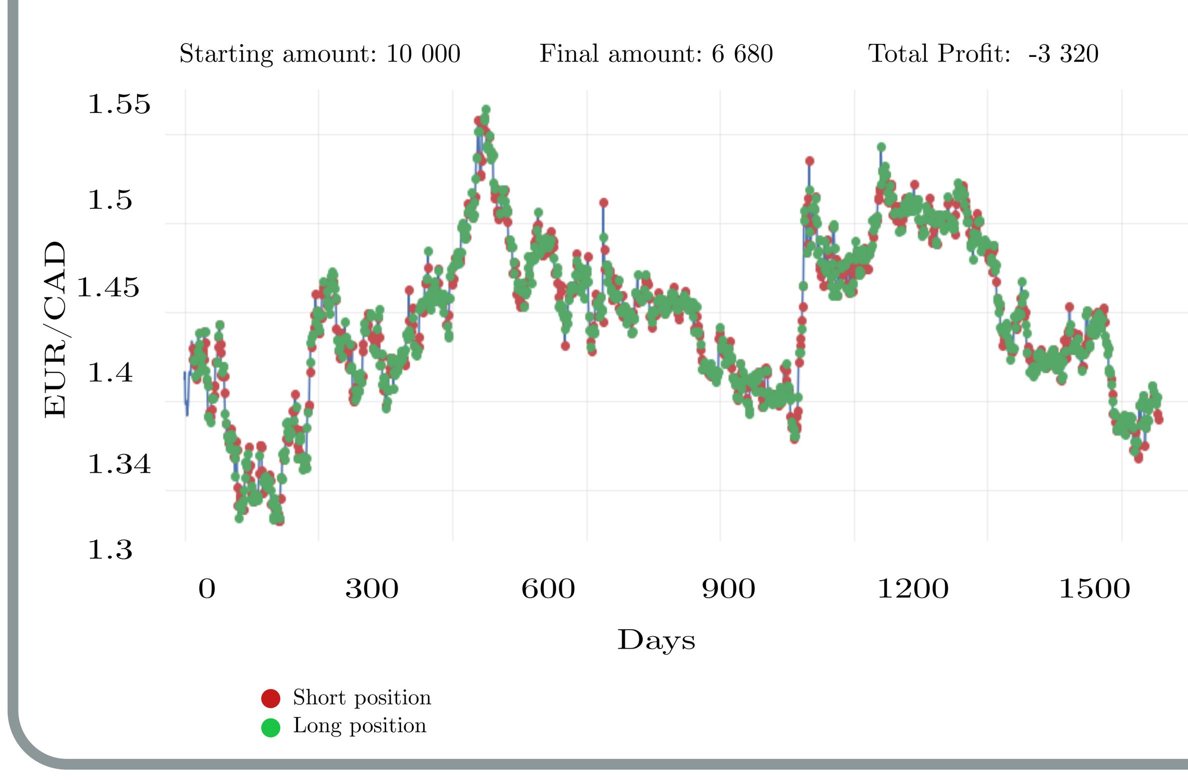
We propose an algorthimic trading framework consisting of a *graphical user interface* component via which a user may specify input data to the framework and a *preprocessing* component which transforms the user-specified data into an appropriate format which is then passed as input to the next component, the *reinforcement learning* component. This component utilises the preprocessed data to create a reinforcement learning trading model which is implemented in a *live trading* component where the results are evaluated and returned to the user.

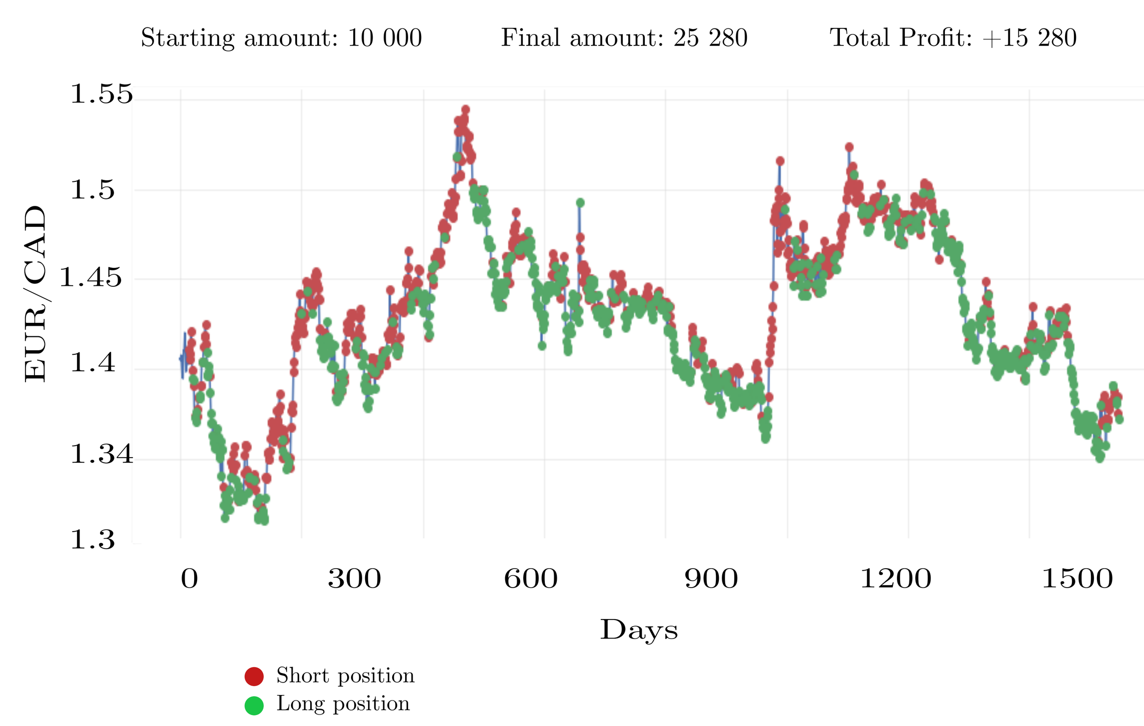
Algorithmic Trading Framework Architecture:



5.Results

We compared the trading results of a random walk against the results of various trained reinforcement learning models embedded in the framework described above. The models were trained and tested on the EUR/CAD currency pair over a five-year period. The results of the Deep Q-learning (DQN) algorithm are shown below. The DQN is one of many deep reinforcement learning algorithms that make use of neural networks and achieves far greater returns, when implemented in a trading environment, compared to a random walk which selects actions at random and mimics the actions of an untrained trader. The results illustrate the promising capabilities of deep reinforcement learning in algorithmic trading.





6. Future work

1. Inclusion of a clustering component into the framework in order to identify and cluster similar market conditions.
2. Implementation of various deep reinforcement learning algorithms in the framework.
3. Carrying out a suite of case studies to test various reinforcement learning algorithms.

7. References

[1] PRASAD, A. *Importance of Machine Learning in Making Investment Decision in Stock Market*, 2021. Vikalpa, **46(4)**, pp. 209–222.

[2] SUTTON RS & BARTO AG. *Reinforcement learning: An introduction*, 2018. MIT Press, Cambridge (MA).