#### Hedging option with Actor Critics methods

#### NTHU DRL Final Project

110062301

資工大三 楊晨鍾

#### 1. Abstract

In this project, I implement a RL model using DDPG to hedge the potential risk of selling a European call option by trading the underlying asset. I used adjusted closed apple stock price from 2012 to 2024 from yahoo finance as my data, the first 80% of the data is for training and the rest are for testing. It reached the same mean price and smaller standard deviation compared to delta hedging using Black-Scholes model.

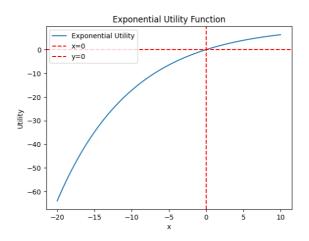
#### 2. Introduction

#### a. European call option

- i. Options are financial derivatives that provide the holder with the right, but not the obligation, to buy or sell an underlying asset at a specified price on or before a specified date.
- ii. A European call option is a type of option that can only be
   exercised at expiration. It allows the holder to buy the underlying
   asset at a predetermined strike price.
- iii. The seller of the call option faces potential risk if the underlying asset's price increases significantly.

#### b. Risk-Averse and Value Function:

 Since the sadness of losing 10 dollars is not equal to the happiness of earning 10 dollars, we need a function to adjust the money. E.g. exponential utility



ii. The goal is to maximize the expected utility of the portfolio's return.

## c. Black-Scholes Model and Delta Hedging:

- i. The model assumes the stock price follow the geometric Brownian motion:  $dSt \coloneqq \mu Stdt + \sigma StdBt, \ 0 \le t \le T$
- ii. By the assumption, we can calculate the call option price and by differentiate by the current stock  $C = SN\left(d_{1}\right) Ke^{-rT}N\left(d_{2}\right)$  price, we know the position we  $d_{1} = \frac{\ln(S/K) + (r + \sigma^{2}/2)T}{\sigma\sqrt{T}} \text{ and } d_{2} = d_{1} \sigma\sqrt{T}$  should hold.  $D = \frac{\partial C}{\partial S_{0}} = N(d_{1})$  Required Inputs:  $S = C \text{ urrent stock price } K = O \text{ ption strike price } T = T \text{ ime remaining until option expiration } T = T \text{ ime remaining until option expiration } T = T \text{ of the stock } T = T \text{ ime remaining until option expiration } T = T \text{ of the stock } T = T \text{ ime remaining until option expiration } T = T \text{ of the stock } T = T \text{ ime remaining until option expiration } T = T \text{ impossible of the stock } T = T \text{ impossible of th$

## d. Reinforcement Learning Approach (DDPG):

DDPG is a is an actor-critic method suitable for continuous action spaces, combining value-based and policy-based methods.

# 3. Methodologies and Implementation

#### a. Data preparation

- Data source: The dataset consists of adjusted closed price of Apple Inc. (AAPL) stock obtain from Yahoo Finance.
- ii. Time Period: The data spans from 2012/1/1 to 2024/1/1.
- iii. Training and testing split: The first 80% of the data is used to training and the rest are for testing.

#### b. Environment setup

- For each episode, I the environment will randomly chooses a path as this time's interacting environment.
- ii. The payoff function is defined as max(StrikePrice, StockPrice)

#### c. Training and evaluation

- State space: (last time step stock price, volatility, current position, time to maturity)
- ii. Action space: 0 to 1, which means the position of the stock.
- iii. Reward function: For each step, the reward is the value gain or loss after that action. And then put that in exponential utility function to get the reward.

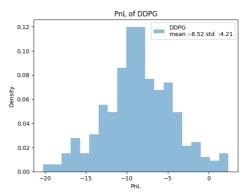
#### 4. Result

DDPG reach roughly the same mean profit and loss and smaller standard deviation compared to Black-Scholes model delta hedging.

#### Black-Scholes delta hedging

# PnL of Delta hedging with Black-Scholes model 0.16 0.14 0.12 0.00 0.00 0.00 0.00 -25 -20 -15 -10 -5

# DDPG



# 5. Conclusion and Future work

- a. During the training process, the DDPG agent will sometimes outperform the Black-Scholes delta hedging, however, it does not converge after training for a long time.
- The training dataset and testing dataset might not be in the same
   distribution, which might lead to the difficulty of training a RL agent.