

# Asset Allocation and Recommendation System

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**Abstract:** The purpose of this project is to design and implement an asset allocation recommendation system to let users buy traditional assets and cryptocurrency at the same time. The system takes in a combined datasets of stock, ETF and cryptocurrencies, and user's preference on value return or risk and acceptable amount of cryptocurrencies. Then the system will give these inputs to two state-of-the-art, model-free reinforcement learning (RL) models, one is the policy gradient model proposed by Jiang et al. and the other is the deep Q-learning model proposed in [12]. Each model will generate a report with suggested purchasing plan (in the form of weight vectors and their corresponding assets) and indicators, the system will choose the strategy that better fits user's preference and output it to the user.

## 1. Background (Review of Related Literature):

### 1. Asset allocation

Asset consists of variable categories such as stocks, bonds, mutual funds, investment partnerships, real estate, cash equivalents, etc. Asset allocation is the idea of dividing given resources among each asset. The investor wants to either maximize the expected return or minimize the expected risk given a certain level of the other factor, thus the agent or software will propose a tradeoff between profits and risks depends on the investor's request. One indicator of the success for a recommendation is the Sharpe ratio, which is by definition the average return minus the risk-free return divided by the standard deviation, the other is the risk level (sometimes shown as volatility) for a range of returns. [4]

Portfolio theory uses the mean-variance pair to evaluate the above factors. The mean is the weighted average of expected return, and the weight is the allocated fraction of investment. The variance is the variance of the expected return of the portfolio. [4] Usually, standard deviation of expected return is another name for volatility, which indicates the risk of the portfolio.

### 2. Reinforcement Learning (RL) methods

Throughout the years, with the maturity of machine learning techniques, financial market trading utilizes more deep machine-learning approaches. Many researches use supervised learning and try to predict trends in price fluctuations, but the performance of these price-prediction-based models relies heavily on prediction accuracy, and the future market prices are usually hard to predict [1]. Some successful attempts of asset allocation algorithms don't predict future prices in the trading problem, instead look at it as a Reinforcement Learning (RL) problem. RL has its way of interacting with the environment and the ability to directly learn the policy of changing the asset weights dynamically in the continuously changing market. Some of the first researches based on RL were done by Moody and Saffel [2] and a recent deep RL utilization by Deng et al. [3] But these methods are limited to single-asset trading, and need more work in order to generate a general asset allocation recommendation when agents trade multiple assets.

In 2009, Xin Du et al. did research on Q-Learning and policy gradient, they found that in comparison to value function based algorithm, the direct RL algorithm provides a simpler problem representation. [9] A step further is Deep Q-learning, which uses a neural network to approximate the Q-value function. It takes in the state and outputs the Q-value of all possible actions. Deep Deterministic Policy Gradient (DDPG) is an algorithm that concurrently learns a Q-function and a policy. It uses off-policy data and the Bellman equation to learn the Q-function, uses the Q-function to learn the policy, and uses actor-critic framework to stabilize the training process and achieve higher sampling efficiency [10].

### 3. Cryptocurrency and RL

Cryptocurrency is under the class of digital currency, it is an electronic and decentralized alternative to government-issued money, with Bitcoin being the first cryptocurrency to use blockchain and the best-known example of a cryptocurrency. Following Bitcoin, more than 1000 altcoins and crypto-tokens have been created and more people consider buying cryptocurrencies as their asset.

In [5], researchers run tests on investment portfolios with Bitcoin being a part of the portfolio, and the result shows that there is an improvement in effectiveness whenever Bitcoin is allocated. Baur, Hong and Lee run the test to compare Bitcoin with 16 other assets including stocks, bonds, energy, currency, and precious metals, their conclusion is: “Bitcoin has the highest return and standard deviation compared to other assets of 7.6%” [6]. A more recent study done using Foreign Currency, Commodity, Stock, ETF and three Cryptocurrencies (Bitcoin, Ripple and Litecoin) with the Modern Portfolio Theory approach to show that cryptocurrency indeed increases the effectiveness of the asset allocation by minimizing the standard deviation and create more allocation options. Another discovery is the “optimum allocation of Cryptocurrency is from 5% to 20% depending on the risk tolerance of the investor”. [7]

Jiang et al. in [1] is one of the first researches that proposes a detailed deep RL framework to work within the cryptocurrency market. They use Ensemble of Identical Independent Evaluators (EIE) topology, a concept of Portfolio Vector Memory to train the network. EIE is a neural network that can evaluate an asset’s potential to grow in near future based on historical data. After calculating the score of each asset, it passes the vector to a softmax layer and computes the new portfolio weights for the next time period.[1] The weights give guidance to the RL agent in making market decisions. The paper also runs tests on different types of EIEs: Convolutional Neural Network (CNN), a basic Recurrent Neural Network (RNN), and Long Short Term Memory (LSTM), and the results show the CNN performs best in final accumulated portfolio value than RNN EIE, LSTM EIE and other trading algorithms.

## 2. Introduction to the Project:

We noticed that recent related works only train their models on one of these two types of assets, and they propose and test their models for that specific asset type while in reality cryptocurrency is growing its popularity and [7] shows adding cryptocurrency to the asset allocation will increase the portfolio’s effectiveness, so more investors will prefer expanding the asset options.

Our project targets to implement an asset allocation recommendation system that gives user a portfolio including both traditional asset and cryptocurrency, and we train the cutting-edge RL model on a combined datasets of S & P 500 stock dataset, ETF (exchange-traded fund) dataset and

cryptocurrency-USD dataset. The users can choose the level of preference on expected return, risk, and a range for the amount of accepted cryptocurrency purchased. The system takes in historical market data, user preference, a finite subset of assets and the agent will generate an internal model of the market. Based on this model and user preference, our system determines a strategy to optimally allocate funds of a finite budget to the available assets and generates a report with the names and amount of assets that the user should invest in.

We will investigate the topic by first searching and reading the proposed models in recent research publications. We agreed upon using the most advanced reinforcement learning algorithms instead of other machine learning techniques as it has shown expressive power and performance advantages. Then we compare the paper and categorize them by model types and the datasets that each model is trained on. Since model-based RL is good when given accurate predictive models and model-free RL is good for chaotic environment dynamics and tractable true objective, our system will choose model-free RL models. Within model-free RL, there are two main approaches: Policy Optimization and Q-Learning. Next, we write down and analyze the pros and cons of specific models within these two types based on performance and modelling efficiency (since we want our recommendation system to deliver fast in-time results to customers). Finally, we will choose two top-ranking models and implement them.

The method we use to choose the reinforcement models are based on datasets diversity. We want to have at least one model with optimal performance in traditional asset datasets, and one model with optimal performance in cryptocurrencies. In addition, we only consider models that take in transaction cost into account and work on multiple assets (ex. not focusing on a single stock), and this criteria help us filter the available RL models. After research, we choose the deep RL with EIIE topology, Policy Gradient (PG) strategy and CNN model in [1] because it achieves better portfolio value and efficiency over benchmarks on cryptocurrency datasets. For the stock market, we are left with DDPG and Deep Q-learning (DQN), but since the model in [1] is a DDPG-like neural network framework, we want to choose the second model as different as the first one, so we pick the valuer-based DQN method. The DQN we use are proposed by Jeong et al. [12], where an agent uses the DQN with a new DNN structure consisting of a branch to learn action values and a branch to learn the number of shares to take.

Some technical challenges are:

1. Incorporate user preference into the portfolio deciding process.
2. Training and tuning two models, since both team members are not familiar with reinforcement learning, so this part will involve lots of studying and experimentation.
3. Construct testing for our recommendation system. Due to lack of experience and knowledge in finance, we need to research different ways of testing the system and find reasonable benchmarks.

### **3. Introduction to the Dataset:**

We plan to use three datasets in our projects: s & p 500 stock dataset, ETF (exchange-traded fund) dataset and a cryptocurrency-USD dataset. Those datasets contain historical price information from the first day of that asset to today.

S & P 500 index is composed of 500 large companies listed on stock exchanges in the United States. We obtained the name (symbols) of those companies from a similar dataset (but a little obsolete) in Kaggle(<https://www.kaggle.com/camnugent/sandp500>), then we used Yahoo! Finance API to get the up-to-date historical price data of those companies. The dataset contains the historical data of all those 500 companies and is about 200M.

For ETF data, we first make use of etfdb (<https://etfdb.com/etfs/country/us/>) to obtain a csv list of about 1500 etf symbols, and then by parsing the csv as the input of Yahoo! finance API, we get historical data of those ETFs. The dataset is also about 200M large.

The procedure of getting cryptocurrency data is a bit tricky. We first discovered a cryptocurrency list in json form on github (<https://github.com/crypti/cryptocurrencies>), then with regard to the API shown in Yahoo! Finance, we did some cleaning on the json file and got about 100 kinds of cryptocurrency-USD historical data via the API. Since most of the cryptocurrencies have a relatively short history, the dataset is about 10M large.

All the data, obtained using python package yfinance(<https://pypi.org/project/yfinance/>), follows the same schema. They all have a date field with Open/Close/Highest/Lowest prices on that day. Some kinds of assets also have 'Dividends' or 'Stock Splits' field, but we would not make use of these fields in our project. And since we use python scripts to get those data, it is very easy for us to obtain the latest price data via the same API. Therefore, we are able to get the newest data as a stream to continuously update our model.

The difficulty in collecting the data are as follows:

1. There are many APIs for fetching financial data, but most of them are not free. It took us a while to find a reliable data source. (the updated Yahoo! Finance API named yfinance)
2. It's difficult to get the name list of all ETFs/stocks/cryptocurrencies. While we are using the python API of Yahoo! Finance to get all the data and the procedure is automatic, it is important to get the whole list of stock/ETF symbols for the program to run. And this procedure is not trivial. We had to do some research and data-processing to make a list fitting the input of Yahoo! Finance API.
3. It's hard to choose which data to use since there are many types of assets. During our research, we found that there are too many types of assets and some of them have complex rules to operate on. So after some consideration, we finally decide to choose some assets that we are most familiar with, and use other assets (mutual funds, foreign currencies) as spare data.

#### **4. Plan:**

We reach the first milestone on Feb. 14, at this point, we will finish writing our proposal, done past literature review, research on different datasets available.

We reach the second milestone on March 14 and we will determine the subset of stocks/cryptocurrencies to use, preprocess datasets for a specific time range in csv or excel format,

design the investor's personality questionnaire and decide how to code it into the RL model, decide two RL models to use in the recommendation system.

We reach the third milestone on April 17. Till then, we will have the core of our several RL models, have the model output correct evaluation factors, train our models, implement the selection process in recommendation system to pick the best asset allocation portfolio among the output of the models.

Between the third milestone and the final presentation, we will keep training and tuning the models, run back-test and user satisfaction test. And improve details of the recommendation system based on our model.

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