risk_dash Documentation

Release 0.0.2

Alexander van Oene

Apr 20, 2021

CONTENTS:

CHAPTER

ONE

RISK_DASH

risk_dash is a framework to help simplify the data flow for a portfolio of assets and handle market risk metrics at the asset and portfolio level. If you clone the source repository, included is a Dash application to be an example of some of the uses for the package.

1.1 Disclaimer: Due to data issues, only up to March 28th EOD is available from Quandl's WIKI EOD Stock Prices found in the example application.

1.1.1 Abstract

While there are many Python packages that provide ways to do data analysis, in fact the package utilizes pandas, numpy, and scipy heavily, there are few that apply and handle common tasks that analysts face in quantifying market risk. pyfolio is one of those packages, however it forces you to utilize their infrastructure package Zipline where as risk_dash aims to provide a framework to formalize the data flow while being totally customizable for the analyst. risk_dash is comprised of classes and methods to handle the data flow and calculation of market risk metrics at the asset and portfolio level. In use, this package should ease the developer's work in building a comprehensive risk analytics application and specifying the underlying risk distribution. This package does not aim to generate trade ideas, but quantify the market risks portfolios of securities face. Included is an example of an application that utilizes this framework focusing on an equity portfolio.

1.1.2 Thesis Steps

First create a framework package, risk_dash, to handle a portfolio of assets, then create a risk application to calculate and display common risk factors and metrics to present common uses for the framework, including: Value at Risk, Expected Portfolio Return and Volatility, Current Return, Systematic risk (Fama - French / CAPM)

To accomplish this task, I am planning on using current research and python packages. I am planning on using Dash by Plotly to create the front end user interface and deploying the underlying Flask app on either DigitalOcean or Heroku

The object model is housed in `~/risk_dash/` where as the application pages are in `~/pages/` and are managed by `/dashapp.py`

While risk_dash only needs a few dependencies,pandas, numpy, scipy,quandl, and requests, the included application uses the dependencies listed in requirements.txt which can be installed by:

```
pip install -r requirements.txt
```

It is highly recommended that you should use a virtual environment when running the package, for details check the Python documentation

1.2 Getting Started - Locally Running the Dash App

First add file `apiconfig.py` to the directory at the same level as `dashapp.py`. That file should contain all of the api information to source the market data. I'm using Quandl so my `apiconfig.py` file is the following:

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

quandl_apikey = 'quandl-api-key' # replace with valid key
```

To use a different market data source, first write a specific `MarketData` class in `market_data.py`

To run the server locally using the underlying Flask Server, run the following command:

```
python dashapp.py
```

If you wanted to use `gunicorn` to run the server, you would just run `gunicorn dashapp:server` from the command line.

1.3 Documentation

Hosted documentation is coming soon. Below is a high level overview of the project:

1.3.1 Object Model

The framework seeks to address a solution to the data pipeline, since the scale is manageable within memory at the moment, that pipeline includes:

- Gathering required data from source systems, i.e. market data, portfolio data, security data
- Managing that data, potentially storing as scale increases
- Manipulating to create new data
- Returning or storing results

To handle that pipeline, the current model is:

- Portfolio
  - Security
- SimulationGenerator
- MarketData
- FundamentalData (Not implemented)

MarketData objects should be the source of the data for a particular Security (or underlier if a derivative security), attributes: - Prices - Source engine (where the data comes from) - Common metrics (first integrated series 'daily price change', shape, dispersion)

SimulationGenerator objects should dictate how any simulation should be conducted, attributes: - Transformation methods - Number of observations - Lookback period, if necessary

Security objects could be any asset, those assets have: - Identification data: Ticker, CUSIP, Exchange - Security specific data: expiry, valuation functions - Market data: Closing prices, YTM - Risk Attributes

The Portfolio object as a collection of Security objects and potentially other Portfolio objects, since we could have different hierarchal structures within the book - This then should house the VCV and common historic market data

1.3.2 File Structure

```
-app.py
-dashapp.py
-pages
  | -- portfolio_metrics.py
  | -- single_ticker.py
-objects
  | -- securities.py
  | -- simgen.py
  | -- market_data.py
```

1.3.3 Current App Features

- Query an individual stock
  - See the past 5 YR candlestick chart
  - See a Monte Carlo simulated vs Historic price distribution
  - View distribution stats
    - Value at Risk for individual stock
    - Annualized vol
    - Annualized Expected Return
    - Simply Weighted/ Exponentially Weighted
  - Variable lookback period
  - Variable sample size
- User upload stock portfolio
  - Mark at current price
  - Calculate portfolio weights

1.3.4 Future App/Package Features

- Expected Return / Variance / Distribution
- Beta to selected market
  - S&P 500
  - Russel 5000
  - Selected ETF
- User selection of MonteCarlo Method
- Option Pricing for individual stock
- Forward looking PDF for Portfolio returns

  - Bayesian modeling
  - ARIMA
- Backtesting tool - common trading strategies
  - “Buy and Hold”

1.4 License

This project is licensed under the the MIT License - see the LICENSE.md file for details

CHAPTER

TWO

RISK_DASH OVERVIEW AND GETTING STARTED

2.1 Overview

risk_dash is a framework to help formalize the data flow for a portfolio of assets and handle market risk metrics at the asset and portfolio level. If you clone the source repository, included is a Dash application to be an example of some of the uses for the package. To run the Dash app, documentation is here

2.2 Installation

Since the package is in heavy development, to install the package fork or clone the repository and run `pip install -e risk_dash/` from the directory above your local repository.

To see if installation was successful run `python -c 'import risk_dash; print(*dir(risk_dash), sep="\n")'` in the command line, currently the output should match the following:

```
$ python -c 'import risk_dash; print(*dir(risk_dash), sep="\n")'
__builtins__
__cached__
__doc__
```

(continues on next page)

(continued from previous page)

```
__file__
__loader__
__name__
__package__
__path__
__spec__
market_data
name
securities
simgen
```

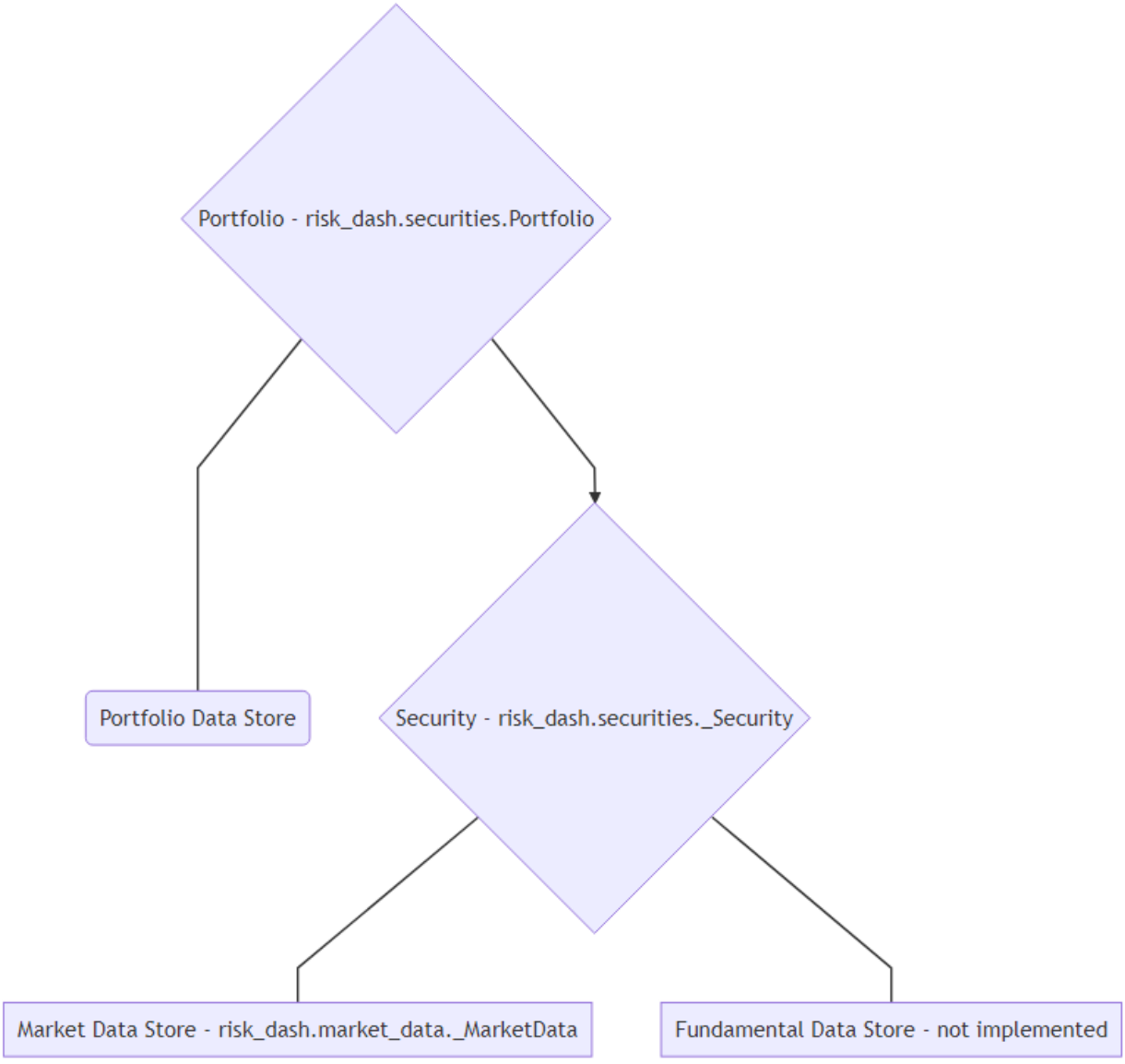
2.3 Getting Started

Now that we have the package installed, let's go through the object workflow to construct a simple long/short equity portfolio.

From a high level, we need to specify:

1. Portfolio Data
    - We need to know what's in the portfolio
        - Portfolio weights
        - Types of Assets/Securities
2. Security data
    - We need to know what is important to financially model the security
        - Identification data: Ticker, CUSIP, Exchange
        - Security specific data: expiry, valuation functions
        - Market data: Closing prices, YTM
3. Portfolio/security constructors to handle the above data

To visualize these constructors, the below chart shows how the data will sit:



To do so, we'll need subclasses for the `_Security` and `_MarketData` classes to model specific types of securities. Currently supported is the Equity subclass. Once we have the portfolio constructed, we will specify and calculate parameters to simulate or look at historic distributions. We'll then create a subclass of `_Simulation` and `_RandomGen`.

2.3.1 Security data, Security objects, and creating Security Subclasses

The core of the package is in the `_Security` and `Portfolio` objects. `Portfolio` objects are naturally a collection of Securities, however we want to specify the type of securities that are in the portfolio. Since we're focusing on a long/short equity portfolio we want to create an Equity subclass.

Subclasses of `_Security` classes must have the following methods:

- valuation(current_price)
- mark_to_market(current_price)
- get_marketdata()

In addition, we want to pass them the associated `_MarketData` object to represent the security's historic pricing data. To build the `Equity` subclass, we first want to inherit any methods from the `_Security` class:

```
class Equity(_Security):

    def __init__(
            self,
            ticker,
            market_data : md.QuandlStockData,
            ordered_price,
            quantity,
            date_ordered
        ):
        self.name = ticker
        self.market_data = market_data
        self.ordered_price = ordered_price
        self.quantity = quantity
        self.initial_value = ordered_price * quantity
        self.date_ordered = date_ordered
        self.type = 'Equity'
```

To break down the inputs, we want to keep in mind that the goal of this subclass of the `_Security` object is to provide an interface to model the Equity data.

- ticker is going to be the ticker code for the equity, such as 'AAPL'
- market_data is going to be a subclass of the `_MarketData` object
- ordered_price is going to be the price which the trade occurred
- quantity for Equity will be the number of shares
- date_ordered should be the date the order was placed

  Note: Currently the implemented `_MarketData` subclass is `QuandlStockData`, which is a wrapper for this Quandl dataset api. This data is no longer being updated, for current market prices you must create a _MarketData subclass for your particular market data.

Required Inputs at the `_Security` level are intentionally limited, for example if we wanted to create a class for Fixed Income securities, we would want more information than this Equity subclass. An example Bond class might look like this:

```
class Bond(_Security):
    def __init__(
            self,
            CUSIP,
            market_data,
```

(continues on next page)

(continued from previous page)

```
            expiry,
            coupon,
            frequency,
            settlement_date,
            face_value
        ):
        self.name = CUSIP
        self.market_data = market_data
        self.expiry = expiry
        self.coupon = coupon
        self.frequency = frequency
        self.settlement_date = settlement_date
        self.face_value = face_value
        self.type = 'Bond'
```

Similarly to the `Equity` subclass, we want identification information, market data, and arguments that will either help in calculating valuation, current returns, or risk measures.

Returning to the `Equity` subclass, we now need to write the valuation and mark to market methods:

```
class Equity(_Security):
  # ...
  def valuation(self, price):
      value = (price - self.ordered_price) * self.quantity
      return(value)

  def mark_to_market(self, current_price):
      self.market_value = self.quantity * current_price
      self.marked_change = self.valuation(current_price)
      return(self.marked_change)
```

For linear instruments such as equities, valuation of a position is just the price observed minus the price ordered at the size of the position. The `valuation` method is then used to pass a hypothetical price into the valuation function, in this case (Price - Ordered) * Quantity, where as `mark_to_market` method is used to pass the current EOD price and mark the value of the position. This is an important distinction, if we had a nonlinear instrument such as a call option on a company's equity price, the valuation function would then be:

$$Value = min\{0, S_T - K\}$$

Where S_T is the spot price for the equity at expiry and K is the strike price of the call option contract. Valuation also is dependent on time for option data, however if you were to use a binomial tree to evaluate the option, you would want to use this same value function and discount the value a each node back to time=0.

Our mark to market then would need to make the distinction between this valuation and the current market price for the call option. The mark would then keep track of what the current market value for the option to keep track of actualized returns.

The final piece to creating the Equity subclass is then to add a `get_marketdata()` method. Since we just want a copy of the reference of the `market_data`, we can just inherit the `get_marketdata()` from the `_Security` parent class.

The `Equity` subclass is already implemented in the package, we can create an instance from `risk_dash.securities`. Let's make an instance that represents an order of 50 shares of AAPL, Apple Inc, at close on March 9th, 2018:

```
>>> from risk_dash.market_data import QuandlStockData
>>> from risk_dash.securities import Equity
```

(continues on next page)

(continued from previous page)

```
>>> from datetime import datetime
>>> apikey = 'valid-quandl-apikey'
>>> aapl_market_data = QuandlStockData(
  apikey = apikey,
  ticker = 'AAPL'
)
>>> aapl_stock = Equity(
  ticker = 'AAPL',
  market_data = aapl_market_data,
  ordered_price = 179.98,
  quantity = 50,
  date_ordered = datetime(2018,3,9)
)
>>> aapl_stock.valuation(180.98) # $1 increase in value
50.0
>>> aapl_stock.mark_to_market(180.98) # Same $1 increase
50.0
>>> aapl_stock.market_value
9049.0
>>> aapl_stock.marked_change
50.0
>>> vars(aapl_stock)
{'name': 'AAPL',
 'market_data': <risk_dash.market_data.QuandlStockData at 0x1147c2668>,
 'ordered_price': 179.98,
 'quantity': 50,
 'initial_value': 8999.0,
 'date_ordered': datetime.datetime(2018, 3, 9, 0, 0),
 'type': 'Equity',
 'market_value': 9049.0,
 'marked_change': 50.0}
```

As we can see `aapl_stock` now is a container that we can use to access it's attributes at the `Portfolio` level.

> Note: Another important observation is that the `Equity` subclass will only keep a reference to the underlying `QuandlStockData`, which will minimize duplication of data. However, at scale, you'd want minimize price calls to your data source, you could then do one call at the `Portfolio` level then pass a reference to that market_data at the individual level. Then your `Equity` or other `_Security` subclasses can share the same `_MarketData`, you would then just write methods to interact with that data.

Now that we have a feeling for the `_Security` class, we now want to build a Portfolio that contains the `_Security` instances.

2.3.2 Portfolio Data and creating a Portfolio

To iterate on what we said before, an equity position in your portfolio is represented by the quantity you ordered, the price ordered at, and when you ordered or settled the position. In this example, we'll use the following theoretical portfolio found in `portfolio_example.csv`:

Type	Ticker	Ordered Price	Ordered Date	Quantity
Equity	AAPL	179.98	3/9/18	50
Equity	AMD	11.7	3/9/18	100
Equity	INTC	52.19	3/9/18	-50
Equity	GOOG	1160.04	3/9/18	5

With this example, the portfolio is static, or just one snap shot of the weights at a given time. In practice, it might be useful to have multiple snapshots of your portfolio, one's portfolio would be changing as positions enter and leave thus having a time dimensionality. The Portfolio class could be easily adapted to handle that information to accurately plot historic performance by remarking through time. This seems more of an accounting exercise, risk metrics looking forward would probably still only want to account for the current positions in the portfolio. Due to this insight, the current Portfolio class only looks at one snap shot in time.

With a portfolio so small, it is very easily stored in a csv and each security can store the reference to the underlying market data independently. As such, there is an included portfolio constructor method in the portfolio class from csv, `construct_portfolio_csv`:

```
>>> from risk_dash.securities import Portfolio
>>> current_portfolio = Portfolio()
>>> port_dict = current_portfolio.construct_portfolio_csv(
  data_input='portfolio_example.csv',
  apikey=apikey
)
>>> vars(current_portfolio)
{'port': {'AAPL Equity': <risk_dash.securities.Equity at 0x11648b5c0>,
  'AMD Equity': <risk_dash.securities.Equity at 0x116442c50>,
  'INTC Equity': <risk_dash.securities.Equity at 0x1177b75c0>,
  'GOOG Equity': <risk_dash.securities.Equity at 0x1177bc390>}}
>>> vars(current_portfolio.port['AMD Equity'])
{'name': 'AMD',
 'market_data': <risk_dash.market_data.QuandlStockData at 0x11648b2e8>,
 'ordered_price': 11.699999999999999,
 'quantity': 100,
 'initial_value': 1170.0,
 'date_ordered': '3/9/18',
 'type': 'Equity'}
```

At this moment, the `current_portfolio` instance is only a wrapper for it's `port` attribute, a dictionary containing the securities in the `Portfolio` object. Soon we'll use this object to mark the portfolio, create a simulation to estimate value at risk, look at the covariance variance matrix to calculate a parameterized volatility measure, and much more.

The `Portfolio` class handles interactions with the portfolio data and the associated securities in the portfolio. If you have a list of securities you can also just pass the list into the `Portfolio` instance. The following code creates a portfolio of just the AAPL equity that we created earlier:

```
>>> aapl_portfolio = sec.Portfolio([aapl_stock])
>>> vars(aapl_portfolio)
{'port': {'AAPL Equity': <risk_dash.securities.Equity at 0x1164b2e80>}}
```

If we want to add a security to this portfolio, we can call the `add_security` method, to remove a security we call the `remove_security` method:

```
>>> amd_market_data = QuandlStockData(
  ticker='AMD',
  apikey=apikey
)
>>> amd_stock = Equity(
  ticker = 'AAPL',
  market_data = amd_market_data,
  ordered_price = 11.70,
  quantity = 100,
  date_ordered = datetime(2018,3,9)
)
```

(continues on next page)

(continued from previous page)

```
>>> aapl_portfolio.add_security(amd_stock)
>>> aapl_portfolio.port
{'AAPL Equity': <risk_dash.securities.Equity at 0x1164b2e80>,
 'AMD Equity': <risk_dash.securities.Equity at 0x11791cc88>}
>>> aapl_portfolio.remove_security(amd_stock)
>>> aapl_portfolio.port
{'AAPL Equity': <risk_dash.securities.Equity at 0x1164b2e80>}
>>> aapl_portfolio.remove_security(aapl_stock)
>>> aapl_portfolio.port
{}
```

2.3.3 Calculating Risk Metrics and Using the Portfolio class

Now that we have our `Portfolio` constructed with the securities we have on the book, let's use the class to calculate some market risk metrics.

Marking the Portfolio

Let's first mark the current portfolio. Since we want to know the current value of the portfolio, the mark method will calculate the value of the portfolio at the current price for each security. The current price is going to be the last known mark, the price at the closest date to today.

> Note: Since the `QuandlStockData` source hasn't been updated since 3/27/2018, we would expect the last shared date to be 3/27/2018. However, you should use the last shared date as a flag to see if an asset's `_MarketData` isn't updating. With certain assets, such as Bonds or illiquid securities, marking daily might not make as much sense, so common shared date doesn't mean as much.

```
>>> current_portfolio.mark()
>>> vars(current_portfolio)
{'port': {'AAPL Equity': <risk_dash.securities.Equity at 0x10f8b2940>,
  'AMD Equity': <risk_dash.securities.Equity at 0x1a1f6b0908>,
  'INTC Equity': <risk_dash.securities.Equity at 0x110538d30>,
  'GOOG Equity': <risk_dash.securities.Equity at 0x110548e10>},
 'market_change': -1476.6999999999989,
 'marked_portfolio': {'AAPL Equity': (8999.0, 8417.0),
  'AMD Equity': (1170.0, 1000.0),
  'INTC Equity': (-2609.5, -2559.5),
  'GOOG Equity': (5800.1999999999998, 5025.5)},
 'date_marked': Timestamp('2018-03-27 00:00:00'),
 'initial_value': 13359.700000000001}
```

The `mark` method now creates the `marked_portfolio` dictionary that stores a tuple, (initial_value, market_value), for every security in the portfolio. We also now can calculate a quick holding period return:

```
>>> holdingreturn = (current_portfolio.market_change)/current_portfolio.initial_value
>>> print(holdingreturn)
-0.11053391917483169
```

This hypothetical portfolio apparently hasn't performed over the month since inception, it's lost 11%, but let's look at historic returns before we give up on the portfolio. We can call `portfolio.quick_plot` to look at a `matplotlib` generated cumulative return series of the portfolio. If you wanted more control over plotting, you could use the returned `pandas DataFrame`. In fact, the current implementation is just using the `pandas DataFrame` method `plot()`:

```
>>> marketdata = current_portfolio.quick_plot()
```

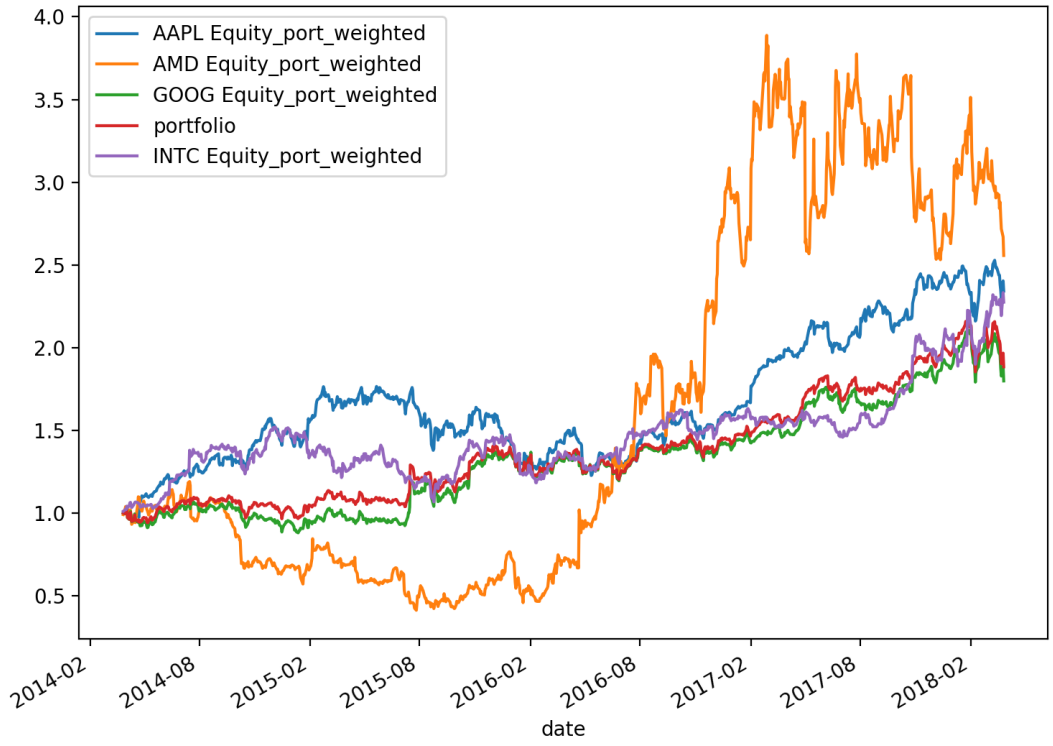


Fig. 1: quick_plot() Output

Parametrically Calculating the Value at Risk

As we can see, this portfolio is pretty volatile, but has almost doubled over the last four years. Let's calculate what the portfolio daily volatility over the period based off the percent change by calling `get_port_volatility` using `percentchange` from the `market_data`:

```
>>> variance, value_at_risk = current_portfolio.set_port_variance(
  key = 'percentchange'
)
>>> volatility = np.sqrt(variance)
>>> print(volatility)
0.01345831069378136
>>> mean = np.mean(current_portfolio.market_data['portfolio'])
>>> print(mean)
0.0007375242310493472
```

We calculated 1.3% daily standard deviation or daily volatility, if the distribution is normally distributed around zero, then we would expect that 95% of the data is contained within approximately 2 standard deviations. We can visually confirm, as well as look to see if there are other distributional aspects we can visually distinguish:

```
>>> import matplotlib.pyplot as plt
>>> marketdata['portfolio'].plot.hist(bins=20,title='Portfolio Historic Returns')
>>> plt.axvline(temp * 1.96, color='r', linestyle='--') # if centered around zero,␣
↪then
>>> plt.axvline(-temp * 1.96, color='r', linestyle='--') #
```

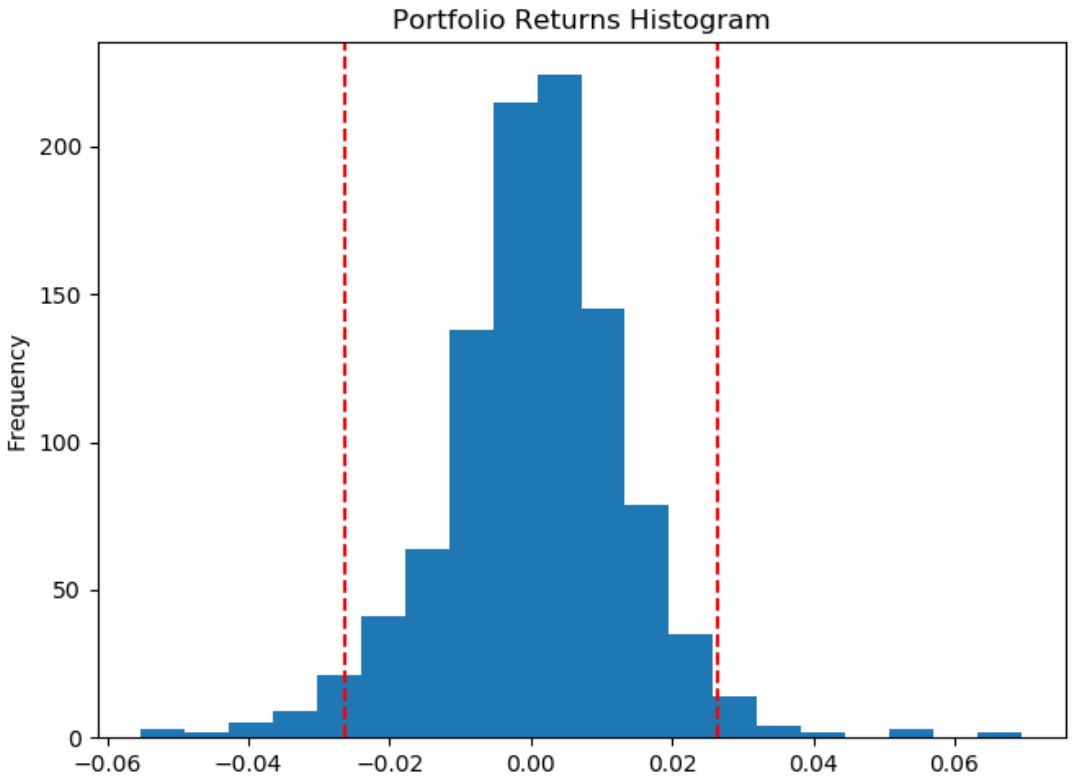


Fig. 2: Portfolio Returns

This distribution looks highly centered around zero, which could signal kurtosis. This seems indicative of equity data, especially for daily returns. Right now, a good place to start thinking about metric parameterization is to assume normality and independence in daily returns. While this assumption might not be very good or might vary between security to security in the portfolio, which we can account for in simulation or purely using historic returns to calculate risk metrics, we can use this distribution assumption to quickly get a Value at Risk metric over a time horizon.

The default time horizon is 10 days at a 95% confidence level for the `set_port_variance` method, so if we look at the returned `value_at_risk`:

```
>>> print(value_at_risk)
-0.083413941112170473
```

This value is simply the standard deviation scaled by time, at the critical value specified:

$$VaR_{t,T} = \sigma \cdot \sqrt{T-t} \cdot Z^*_{p=\alpha}$$

We can interpret this Value at Risk as being the lower bound of the 95% confidence interval for the 10 day distribution.

For this portfolio, on average, a loss over 10 days less than 8.3% should occur 2.5% of the time. To get the dollar value of the 10 Day Value at Risk, we would just multiply this percent change by the current portfolio market value.

```
>>> dollar_value_at_risk = value_at_risk * (current_portfolio.initial_value + current_
↪portfolio.marked_change)
>>> print(dollar_value_at_risk)
-991.20786223592188
```

Similarly, we could interpret as over the a 10 day period, on average, 2.5% of the time there could be an approximate loss over $991.21 dollars for this portfolio. However, this is relying on the assumption that the portfolio is: a) normally distributed, and b) daily returns are serially independent and identically distributed. One way we can go around this is to look at the historic distribution

```
>>> historic_distribution, historic_var = current_portfolio.historic_var()
>>> print(historic_var)
-0.073051970330112487
```

This is calculated by doing a cumulative sum of returns over each horizon time period, then taking the appropriate percentile of the distribution to get a VaR based on historic prices. This is is smaller than the parametric VaR due to the fact that the distribution looks more right skewed as shown below

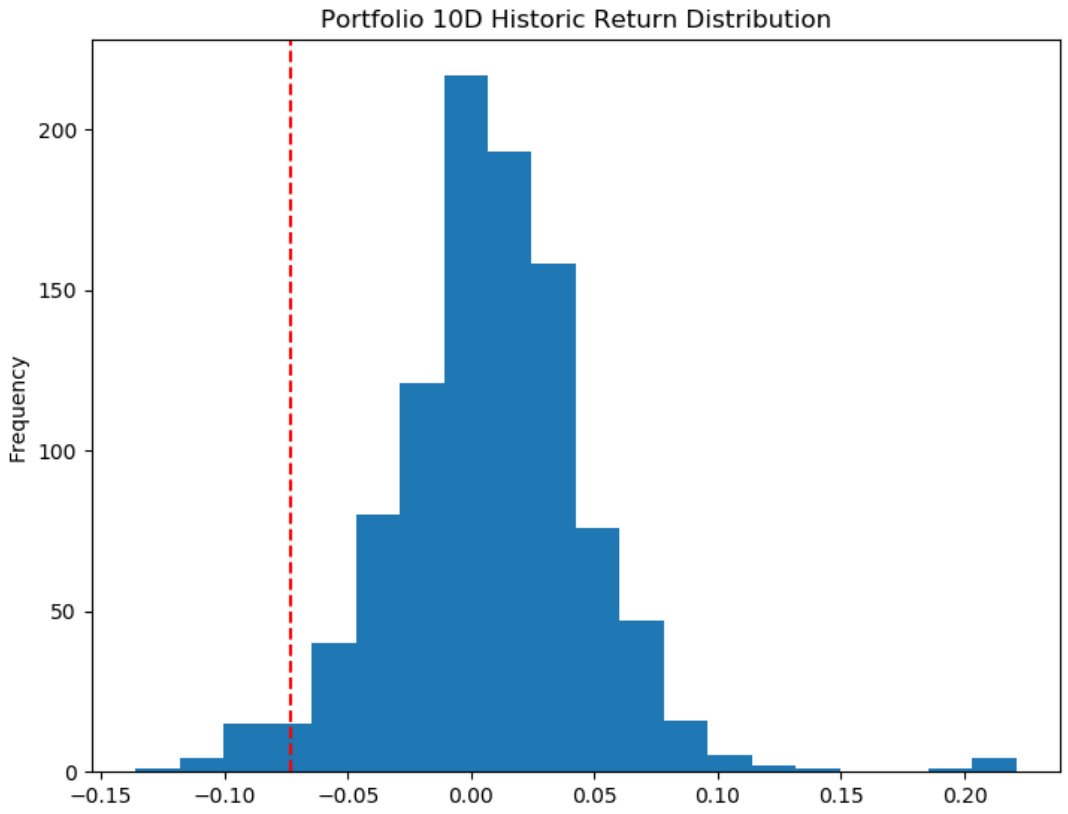


Fig. 3: Historic 10D VaR

This method is fairly simple, however it is based on the assumption that the previous distribution of outcomes is a good representation of the future distribution.

Another way we've implemented to calculate the value at risk is to simulate the portfolio distribution.

2.3.4 Simulating the Portfolio

When simulating portfolio returns, one's objective is to correctly specify the portfolio distribution. I consider two major approaches, "bottom-up" and "top-down".

The "bottom-up" approach would include simulating the underlying securities first and then valuing the portfolio through the simulated distributions. The major strength of this method is the ability to easily value the effect of derivative securities on the portfolio. Since one would simulate the derivative's underlier, you could easily then apply the associated value function through the simulated distribution to get the security's profit and loss distribution. Another benefit to this methodology is the analyst has the freedom to change the simulation process at a security level. General Brownian motion might be a good assumption for long/short equity positions, but maybe not as good when simulating yield curves for bonds. Another strength would be the ability to change portfolio weights of securities post simulation, if you simulate a base unit of the security you could then scale the weights accordingly to easily reweigh the portfolio. The biggest challenge to this methodology is to ensure that each simulation value represents the same market environment, meaning that each simulation pull represents the same environment state. While you can potentially do a convolution of the different simulations to get a representative joint distribution of the portfolio, you must ensure that one is capturing the covariance between the securities. For example, equities and bonds have historically had negative correlation to each other, thus a portfolio containing both would potentially have a lower variance than each security separate. To capture that in a simulation one would have to simulate directly from the variance-covariance matrix or do a convolution to combine separate simulations together. While both are possible, and in practice it is probably a preferred methodology, however it's not within the scope of this project.

The "top-down" approach would include aggregating the portfolio a priori and then simulating that distribution. Since the portfolio is made of the member securities, thus the aggregated distribution represents all covariance. While this method gets a little be trickier to handle with derivative securities, since you would need historic market prices per contract and potentially roll adjust through the time period, for securities like equities the assumption seems arguable. The benefit of this method would be having to deal with one simulation and verifying if it represents the underlying distribution vs having several different simulations and verifying if they accurately represent the covariance of constituent securities. The drawback is having less flexibility in the modeling of individual securities within the portfolio. Another drawback is to change the weighting or portfolio members, one must recombine and simulate the new portfolio, which could be computationally intensive depending on the methodology.

Either way, to implement simulation, the `_Simulation` and `_RandomGen` class that handle the calculation and generation respectfully. For example, to implement a naive return model, the included `NaiveMonteCarlo` class represents the following generation function for a single observation:

$$R_t = \phi$$

Where ϕ representing a pull from an imposed distribution. As such, we need to specify that imposed distribution, thus we include the `NormalDistribution _RandomGen` class to generate a pull. This class is just a wrapper to for numpy.random.normal with the mean and standard deviation specified in the initialization.

Since the aim is to specify the portfolio distribution X days into the future, we want to simulate a cumulative return path through time. Under the assumption that each day is independent, the individual simulation path is then:

$$P = \sum_{t=1}^{X} R_t = \sum_{t=1}^{X} \phi$$

Now to fully specify the distribution via a Monte Carlo process, we will generate Y paths to represent the underlying X day distribution. To get the mean of the distribution at each t step from 1 to X:

$$E(R_t) = \frac{1}{Y} \sum_{i=1}^{Y} P_{t,i} + E((R_{t-1}))$$

To get the variance:

$$Var(R_t) = E\left((R_t - E(R_t))^2\right) + Var(R_t) = \frac{1}{Y^2}\sum_{i=1}^{Y}\left(P_{t,i} - \bar{P}_t\right)$$

Since each return is assumed independently and identically distributed, the above condenses to:

$$Var(R_t) = t \cdot Var(R_t)$$

Since we can now switch out the distribution of ϕ to represent the portfolio or constituent securities, this generation function is agnostic of which approach explained above is taken. It's for that reason the design choice was made to make the `_RandomGen` and `_Simulation` classes seperate instead of building methods directly into the `Portfolio` or `_Security` class.

Simulating a Unit Resolution Distribution

First let's simulate a unit resolution distribution. By default, the resolution is one day, but depending on the market data resolution you could simulate to match. Since the default is one day, let's simulate a one day distribution and then simulate a X day forward path distribution using `aapl_stock`:

```
>>> from risk_dash.simgen import NormalDistribution, NaiveMonteCarlo
>>> log_return_generator = NormalDistribution(
    location = aapl_stock.market_data.currentexmean,
    scale = aapl_stock.market_data.currentexvol
  )
```

Since we're just simulating one day, we can directly use the generator object simulate a one day return distribution. With our new `log_return_generator` instance, we are assuming a normally distributed return series. By default, using `currentexmean` will center the distribution around the closest 80 day exponentially weighted mean of daily AAPL returns. Similarly, using `currentexvol` will set the standard deviation to the closest 80 day exponentially weighted standard deviation of historic daily AAPL returns. To simulate one pull now from a normal distribution, we have an observation that represents a log return of AAPL.

```
>>> log_return_generator.generate(1)
array([-0.00948158])
```

One observation isn't really helpful for us, we now want to simulate an arbitrarily large amount of observations to converge to the underlying distribution. In this case, let's simulate 5000 observations:

```
>>> import numpy as np
>>> one_day_simluation = log_return_generator.generate(5000)
>>> len(one_day_simulation)
5000
>>> np.mean(one_day_simluation)
-0.00036139846164594291
>>> aapl_stock.market_data.currentexmean
-0.00040076765463907944
>>>np.std(one_day_simulation)
0.016497493178538599
>>>aapl_stock.market_data.currentexvol
0.016485817752205818
```

To parameterize the sampling distribution of the distribution, we can simulate an arbitrarily large amount of simulations to converge to the sampling distribution:

```
>>> multiple_one_day_simulations = np.array([log_return_generator.generate(5000) for
↪i in 5000])
>>> np.mean(np.mean(multiple_one_day_simulations, axis = 0)) # sampling distribution
↪mean of the simulation mean
-0.00039625427660093282
>>> np.std(np.mean(multiple_one_day_simulations, axis=0))
0.00023461080665209953
>>> np.mean(np.std(multiple_one_day_simulations, axis=0))
0.016484835778989758
>>> np.std(np.std(multiple_one_day_simulations, axis=0))
0.00016629650698145025
```

With the mean and standard deviation of the sampling distribution we can construct confidence intervals to see if our calculated mean and variance is contained. This would imply we have specified the imposed distribution based on our calculation of `currentexvol` and `currentexmean`. The calculation for a 95% confidence level is:

$$\bar{X} \pm Z^*_{p=\alpha} \frac{s}{\sqrt{n}}$$

So for this case, for a 95% confidence level, $1 - \alpha$, our confidence interval for the simulation mean is (-0.0004027, -0.0003897) and for the simulation standard deviation is (0.0164802, 0.0164894). Our calculated historic values, -0.0004007 and 0.0164858, both fall within those confidence intervals so at the 95% confidence level we can determine this simulation represents a normally distributed one day return series.

Simulating a Path Distribution

To simulate a forward return path of independent returns, we now want to create a `NaiveMonteCarlo` object to simulate Y forward resolution paths.

```
>>> simulation_generator = NaiveMonteCarlo(log_return_generator)
```

The `NaiveMonteCarlo` accepts any `_RandomGen` object, so we could potentially pass a `_RandomGen` object that might more accurately represent our underlying data. For example, if we thought that AAPL was distributed with a Cauchy distribution to capture fatter tails, we could pass in a `_RandomGen` object that represented the distribution. Now we'll maintain the assumption that the log returns are normally distributed and use the `generator` instance we created earlier.

To simulate 5000 paths for a 5 day forward distribution, we would then call the `simulate` method passing the arguments `periods_forward=5` and `number_of_simulations=5000`. This will set the `simulation_mean`, `simulation_std`, and `simulated_distribution` attributes and return the simulated distribution.

```
>>> path_simulation = simulation_generator.simulate(periods_forward=5, number_of_
↪simulations=5000)
>>> path_simulation.shape
(5000,5)
>>> simulation_generator.simulation_mean
array([-0.00050452, -0.00082389, -0.00105195, -0.00135753, -0.0019303 ])
>>> simulation_generator.simulation_std
array([ 0.01630096,  0.02311434,  0.0283451 ,  0.03211978,  0.03607576])
```

The simulation distribution now is 5000 individual 5 day paths, represented as a `numpy` array of shape (5000,5). The `simulation_mean` and `simulation_std` are then calculated across the column axis, giving us the simulated generation through time. Since this method is fairly naive, essentially the cumulative sum of independent random normals, it makes sense that the `simulation_mean` vector is essentially $E(R_t) = t \cdot E(R_{t=1})$ and $S.D.(R_t) = \sqrt{t} * S.D.(R_{t=1})$. If we wanted to implement a more standard approach of simulating returns, we could then create a `_Simulation` class that would represent the value function. To simulate the portfolio from the top down approach, we would then just use the portfolio mean and variance to then simulate the portfolio.

2.4 Summary

While this is just the first introduction to the package, there are many expandable directions to go. The aim for the package is to help formalize the development process by providing clear template classes and use cases. The next steps are to write `_Security` classes that match the portfolio that the analyst is trying to model and `_MarketData` classes that match the specific data store for the application.

CHAPTER

THREE

RISK_DASH DASH APPLICATION DOCUMENTATION

3.1 Overview

The included Dash application is purely to demonstrate a use case for the `risk_dash` package. There is minimal css provided through using Bootstrap and the Dash Bootstrap Components python library. For a complete overview of Dash, please check the respective documentation, as this will be very high level and explain the basics of how the sample application works.

3.2 Getting Started - Locally Running the Dash App

3.2.1 Dash applications

To quote the Dash documentation:

> Dash is a productive Python framework for building web analytic applications. Written on top of Flask, Plotly.js, and React.js, Dash is ideal for building data visualization apps with highly custom user interfaces in pure Python. It's particularly suited for anyone who works with data in Python.

Due to it's lightweight nature and pure python syntax, it's a great use case to show off the functionality of the `risk_dash` framework. Dash applications are typically single purpose and leverage `plotly.js` for it's graphic capabilities. This application is structured in a way to have multiple pages using JavaScript callback functionality. These pages are rendered in the `app.layout` found in `dashapp.py`, then when an HTTP request is then made to the `Flask` server, the application's callback structure then updates the HTML Div container on the main index page and renders the according webpage. Each HTML and interactive object is referenced by it's `id` attribute, so

each callback uses those references to pass along data and respond interactively. For this Dash application, the main callback function is taking the individually described page layouts and displaying them in the main `Div` container.

For example, from `dashapp.py`:

```
@app.callback(
    Output('page_content', 'children'),
    [Input('url', 'pathname')]
)
def get_layout(url):
    if url != None:
        if url == '/portfolio':
            return(portfolio_metrics.layout)
        elif url == '/single':
            return(single_ticker.layout)
        elif url == '/docs':
            return(dcc.Markdown(docs))
        else:
            return(dcc.Markdown(readme))
```

The function takes the URL given as input, then returns the respective HTML object to populate the children attribute of the `page_content` `Div`-like object in the main `app.layout`. The decorator `@app.callback` registers this function with the `app Dash` object, explained *below*.

Since one of the objects of the `risk_dash` framework is to create an in memory risk valuation engine, this included app has two main pages:

- Individual Equity Analysis `single_ticker.py`
  - Shows how the `_Security` and `_MarketData` can be used to value a single security and run a Monte Carlo simulation
- Portfolio Dashboard `portfolio_metrics.py`
  - Shows how the `Portfolio` object can value a collection of `_Security` objects

As seen above, the URL ending in /portfolio/ returns the `portfolio_metrics.layout` member, the /single returns the `single_ticker.layout` member, /docs returns an HTML version of the getting started documentation, and any other URL returns the README.

The file structure of the app is as follows with a bit more detail than the README.md:

```
-app.py # contains server level configurations
-dashapp.py # contains application level routing and main structure
-pages # the layout rendering and callback functions to create each page
  | -- portfolio_metrics.py # displays a portfolio level risk
  | -- single_ticker.py # displays a single equity position risk
-objects # risk_dash framework objects
  | -- securities.py # security objects
  | -- simgen.py # simulation objects
  | -- market_data.py # market data objects
```

To add a page to the application, the process is simple:

- Create a `.py` file that contains the following:
  - A `dash_html_components.Div` object to replace the children of the `app.layout#page_content` named `layout`
  - The respective callback functions to populate the content of the `dash_html_components.Div` and register them with the `app.app` object

- In the `dashapp.py` file, register the desired URL in the `get_layout` function and return the `layout` member of the created `.py` file

3.2.2 The risk_dash Dash object

Referring from the Dash documentation and source code, the Dash object handles all of the rendering of the JavaScript and HTML components of our defined application. This object is defined in `app.py`, where we define a couple of server level configurations. Here are the important definitions below:

```
import dash
import dash_bootstrap_components as dbc

style_sheets = [dbc.themes.BOOTSTRAP] #add in the css stylesheets for Bootstrap
app = dash.Dash(__name__, external_stylesheets=style_sheets,) # main application␣
↪initialization

server = app.server # exposing the underlying Flask server
app.config.suppress_callback_exceptions = True # configuration to suppress exceptions␣
↪relating to the multi-page configuration
```

The defined `app` object is the `Dash` instance that will need to register all of the defined callbacks we create. The `server` object is the underlying `Flask` server instance that hosts and interacts with the incoming HTTP requests. After defining these, we then import them to the `dashapp.py` file that will define the main, application level, functionality.

```
# dash dependencies/modules
import dash_core_components as dcc
import dash_bootstrap_components as dbc
import dash_html_components as html
from dash.dependencies import Input, Output

# application level code
from app import app, server
from pages import single_ticker, portfolio_metrics
# ...

# the main application layout, defines the NavBar and the container that will store␣
↪the rendered HTML from pages
app.layout = dbc.Container(
# ...
)

# if this is run as a script, then run the server
if __name__ == '__main__':
    print('Running')
    app.run_server()
```

When this script is then run with `python dashapp.py` or otherwise, all of the namespaces are loaded in, thus the Dash object registers the defined callbacks with the associated component inputs and HTML outputs and is ready to receive HTTP requests.

Next, we'll briefly talk about how to run the server locally, though it could be deployed on a remote server and receive HTTP requests over the broader internet.

3.2.3 Running the application locally

To run the server locally using the underlying Flask Server, run the following command:

```
python dashapp.py
```

This runs the file as a script, loads in the necessary namespaces, and calls the `app.run_server()` method. Additonally, since the `Flask` app isn't intended to be a production server, in a production environment we might want to use `gunicorn` to run the server. We would just run `gunicorn dashapp:server` from the command line instead. Running the server with the `Flask` app locally for testing and proof of concept, calling `python dashapp.py` will run the server on the default port/local ip address, http://127.0.0.1:8050/, where you can then open the application in a web browser like Chrome.

3.3 Application Usage

3.3.1 Individual Equity Analysis Page - single_ticker.py

The intent for this page is to show the functionality of the `_MarketData` and `Equity` classes, with a simple data query and simulation run. The page is configured to run a Naive Monte Carlo simulation with a normal random walk, and a historic price simulation for comparison. The user puts in the ticker they want to evaluate, then the server calls the following callbacks:

- `get_data`
  - Creates a MarketData object by calling the Quandl API for a given stock ticker from the `dash_core_components.Input` labeled 'stock' and is called when the user hits the button labeled 'Run'
  - Creates a simulation object from the MarketData and computes a simulation and evaluates some metrics to be used later
  - Stores the data in hidden `<div>` as a json object
- `chart`
  - Takes the queried MarketData, appends the forward steps of the configured Monte Carlo simulation and plots it as a time series
- `monte_carlo_histogram`
  - Takes the evaluated simulation data and plots it as a histogram
- `summary_table`
  - Takes the evaluated metrics and displays them as a HTML table

Here is a screenshot of the output from the `get_data`, `chart`, `monte_carlo_histogram`, and `summary_table` call backs

Again, the HTML layout is defined by the defined layout object, that contains the `dash` components to render the HTML and JavaScript as needed. In the future, this could be extended

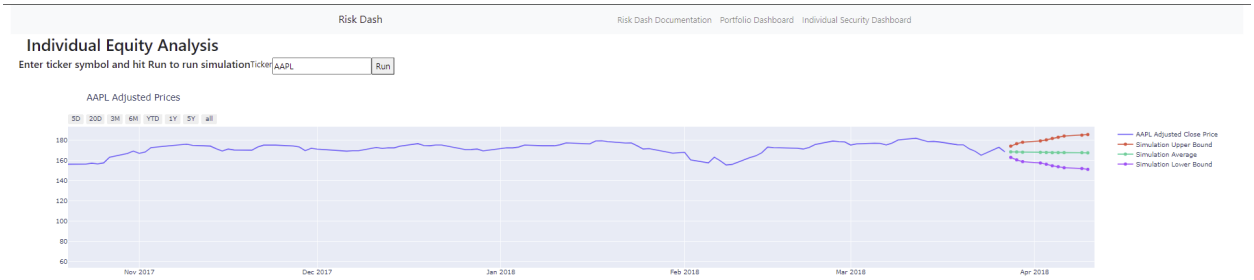


Fig. 1: Time Series plot for AAPL Adjusted Closing Prices

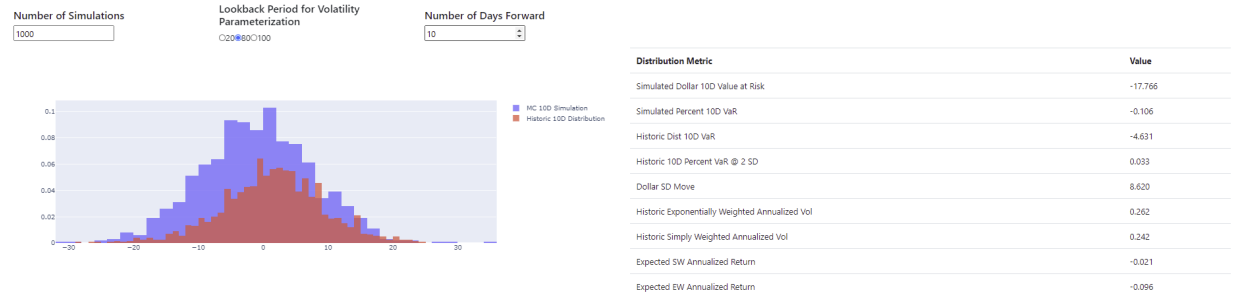


Fig. 2: Histogram plot for AAPL Monte Carlo Simulation

3.3.2 Portfolio Metrics - portfolio_metrics.py

The intent for this page is to show the functionality of the `Portfolio` class, which is a collection of `Equity` object instances. An extension of this project could be to extend the object and run independent and correlated simulations as described in the getting started docs. The user uploads a portfolio from a csv file, then the page pulls all the required data and evaluates the current value of the portfolio. When uploaded, the following callbacks are called:

- `output_upload`
  - When a portfolio csv is uploaded, then a `Portfolio` object is created and the underlying market data is queried.
- `displayport`
  - Once the data is queried and stored, some simple metrics are calculated and displayed in the HTML table

Here is a screenshot of the upload element

Fig. 3: Portfolio Upload and Template Download

Here is the sample portfolio found in ‘./portfolio_example.csv’

Ticker	Current Price	Initial Value	Market Value	Return %
AAPL	168.34	8999	8417	-6.467385265029447
AMD	10	1170	1000	-14.529914529914532
INTC	51.19	-2609.5	-2559.5	1.9160758766047135
GOOG	1005.1	5800.2	5025.5	-13.356435984966033
Total		13359.7	11883	-11.053391917483182

Fig. 4: HTML Table with Theoretical Portfolio Valuation

3.4 Summary

This lightweight application is not intended to be the only use of the `risk_dash` framework, but to show the initial possibilities of using an in memory risk engine that is lightweight enough to value simple and complex securities.

CHAPTER

FOUR

RISK_DASH.SECURITIES

class risk_dash.securities.**_Security**(*name*, *market_data:* risk_dash.market_data._MarketData, ***kwargs*)

Template for _Security subclasses

get_marketdata()

Helper function to return market_data attribute

Returns self.market_data

mark_to_market(*current_price*)

Function to value current _Security with current prices, marking the value to current prices

Parameters **current_price** – float, represents the current price for the _Security

Returns float, the value of the _Security at current market price

simulate(*SimulationGenerator*, *periods_forward*, *number_of_simulations*)

Function to run simulation on a _Security based level

valuation(*price*)

Function to return the value of _Security at a given price

Parameters **price** – float, the price to value the _Security

Returns float, the value of the _Security given price

class risk_dash.securities.**Equity**(*ticker*, *market_data:* risk_dash.market_data.QuandlStockData, *ordered_price*, *quantity*, *date_ordered*)

The Equity class represents an equity position in a publically traded company

Parameters

- **ticker** –
- **market_data** –
- **ordered_price** –
- **quantity** –
- **date_ordered** –

mark_to_market(*current_price*)

Returns the current value of the Equity given current price

Parameters **current_price** – float, represents the current price of the Equity Security

Returns the value of the Equity at current market prices

simulate(*SimulationGenerator*, *periods_forward*, *number_of_simulations*)

Function to run simulation at the Equity based level

valuation(*price*)
Returns value of the Equity given price input. Equity value is linear depending on a buy or sell, multiplied by the quantity of the position

Parameters **price** – float, represents a given price

Returns the value of the Equity at a given price

class risk_dash.securities.**Portfolio**(*securities=None*, *data_input=None*, *apikey=None*)
The Portfolio class handles interactions with the portfolio data and the associated securities in the portfolio.

Parameters

- **securities** – list of _Security objects or None, if None, the object will try to create the port attribute using other data, if a list it will use the list of _Security objects
- **data_input** – pandas.DataFrame, str, or None. If None and securities is None, no port attribute will be made and be an empty portfolio. Either pandas DataFrame or string path to a portfolio matching './portfolio_example.csv'
- **apikey** – str, ApiKey for the market data object

add_security(*security*, *overwrite=True*)
Helper function to add _Security object to port attribute

Parameters **security** – _Security, _Security object to add to port dictionary

calculate_portfolio_returns(*market_data*)
Calculates market data returns from flat prices

Parameters **market_data** – the market_data variable with a flat price values

Returns the market_data variable with log returns

construct_portfolio_csv(*data_input*, *apikey*)
Built in portfolio constructor method

Parameters

- **data_input** – either pandas DataFrame or string path to a portfolio matching './portfolio_example.csv'
- **apikey** – ApiKey for the market data object

Returns dict for self.port

drawdown(*market_data=None*, *returns=True*, *key='adj_close'*)
Calculate Draw Down, the previous peak to current trough, through the historic market data

Parameters

- **market_data** – DataFrame, the portfolio level market_data. Use if made external changes to the market_data
- **returns** – Bool, True if calculate DD based on continuous returns, False if on level prices
- **key** – string, corresponds to the market_data column to be calculated

Returns DataFrame representing the Draw Down for the portfolio and components

get_date()
Grab the security with the most dates.

Returns returns a DatetimeIndex to construct a shared portfolio market_data DataFrame

get_last_shared_date()
Return the last shared date

Returns DateTime object

get_port_variance(*recalc=False*, *confidence_interval=0.39881763041638185*, *var_horizon=10*, *lookback_periods=0*, *key=None*)
Returns portfolio variance

Parameters

- **recalc** – bool, If True recalculate variance
- **confidence_interval** – float, The critical value to implement parametric VaR
- **var_horizon** – int, how many days/periods forward the parametric VaR should be calculated
- **lookback_periods** – int, how many days/periods backward to condition the underlying distribution
- **key** – string, corresponds to the market_data column to be calculated

Returns tuple: (float Var(Portfolio), float Parametric Portfolio V@R)

get_portfolio_marketdata(*key=None*, *recalc=False*)
Returns self.market_data

Parameters **key** – If not set, use key to set market_data

Returns pandas DataFrame self.market_data

get_weights()
Returns self.weights

Returns dict for each security weight

historic_var(*market_data=None*, *returns=True*, *key='adj_close'*, *confidence=2.5*, *var_horizon=10*)
Calulate Value at Risk from the historic distrubtion

Parameters

- **market_data** – DataFrame, the portfolio level market_data. Use if made external changes to the market_data
- **returns** – Bool, True if calculate DD based on continuous returns, False if on level prices
- **key** – string, corresponds to the market_data column to be calculated
- **confidence** – float, percentile in percentage to pass into np.percentile
- **var_horizon** – int, how many days/periods forward the parametric VaR should be calculated

Returns tuple, (DataFrame, market_data, float, Historic VaR)

mark()
Mark portfolio with current market prices, sets marked_portfolio and market_change.

quick_plot(*returns=True*, *key='adj_close'*, *plot=True*, *figsize=(5, 8)*)
Quickly plot using matplotlib and pandas.plot()

Parameters

- **returns** – Bool, True if calculate DD based on continuous returns, False if on level prices
- **key** – string, corresponds to the market_data column to be calculated
- **plot** – Bool, if True, plot the data frame, if flase just return the market_data DataFrame

Returns DataFrame market_data

remove_security(*security=None*, *security_name=None*, *security_type=None*)
Helper function to remove _Security object from port attribute, either pass the object or name type string pair to remove from port dictionary

Parameters

- **security** – _Security, _Security object to remove
- **security_name** – str, Name of the security for .port key, to match _Security.name
- **security_type** – str, String to match _Security.type of the _Security object to be removed

set_port_variance(*market_data=None*, *confidence_interval=-1.9599639845400545*, *var_horizon=10*, *lookback_periods=0*, *key='percentchange'*)
Calulates parametric Variance by calculating Weight.T * Cov * Weight

Parameters

- **market_data** – DataFrame, the portfolio level market_data. Use if made external changes to the market_data
- **confidence_interval** – float, The critical value to implement parametric VaR
- **var_horizon** – int, how many days/periods forward the parametric VaR should be calculated
- **lookback_periods** – int, how many days/periods backward to condition the underlying distribution
- **key** – string, corresponds to the market_data column to be calculated

Returns float portfolio variance, standard deviation ** 2, float parametric value at risk

set_portfolio_marketdata(*key*)
Combine individual market data into one pandas DataFrame.

Parameters **key** – Common column name for each security

Returns pandas DataFrame containing columns for each security's common market_data

set_weights()
Calculate value weighted portfolio.

Returns dict for each security weight

simulate(*SimulationGenerator*, *periods_forward*, *number_of_simulations*)
Primary function to simulate the entire portfolio

value()
Value current portfolio with current market prices.

Returns value of the portfolio

CHAPTER

FIVE

RISK_DASH.MARKET_DATA

class risk_dash.market_data.**_MarketData**
Template for _MarketData subclasses

current_price()
This should return the current market price, the price at the last available time period

Returns float the market price

gather()
This should gather data from the source and store it into memory or dictate how to interact with the source

Returns a pandas DataFrame, market_data or other data type to interact with

class risk_dash.market_data.**QuandlStockData**(*apikey*, *ticker*, *days=80*)
_MarketData class for Quandl's WIKI/EOD price data base (https://www.quandl.com/databases/WIKIP)

Parameters

- **apikey** – string, a valid Quandl apikey
- **ticker** – string, ticker symbol to query
- **days** – int, how many days back to use for rolling metrics

current_price()
Returns the latest available market price

Returns float, latest available market price

gather()
Gathers the data from the Quandl api and returns a pandas DataFrame

Returns pandas DataFrame

set_expected(*days*)
Calculate exponentially and simply weighted rolling averages

Parameters **days** – int, look back days to compute rolling averages

set_price_changes()
Set daily price changes and logged percent changes

set_volatility(*days*)
Calculate exponentially and simply weighted rolling standard deviations

Parameters **days** – int, look back days to compute rolling std deviation

CHAPTER

SIX

RISK_DASH.SIMGEN

class risk_dash.simgen.**_RandomGen**(***kwargs*)
Abstract class for a Random Variable Generator

Parameters **kwargs** – dict, a collection of necessary arguments to specify the RV distribution. See .NormalDistribution for an example

generate(***kwargs*)
Function to generate random values given the RV distribution or other method of generating values

class risk_dash.simgen.**_Simulation**(*Generator:* risk_dash.simgen._RandomGen, ***kwargs*)
Abstract class to create a simulation given a Random Variable Generator

Parameters **Generator** – _RandomGen, the RV distribution to use for a given simulation. See .NaiveMonteCarlo for an example

set_var(*percentile=2.5*)
Helper function to set Value at Risk given a certain percentile

Parameters **percentile** – float, default 2.5, represents the Value at Risk, as defined by a certain percentile, for a simulation

class risk_dash.simgen.**NormalDistribution**(*location*, *scale*)
A _RandomGen object that represents a normal/Gaussian. See [numpy documentation](https://numpy.org/doc/stable/reference/random/generated/numpy.random.normal.html) for more detail

Parameters

- **location** – float, the mean/center of the distribution
- **scale** – float, the standard deviation of the distribution. Must be non-negative.

generate(*obs*)
Function to return a numpy.array of parametrically defined normally distributed random values

Parameters **obs** – int, number of values to be generated

Returns numpy.array of numpy.float, represents a collection of randomly distributed values

class risk_dash.simgen.**NaiveMonteCarlo**(*Generator:* risk_dash.simgen._RandomGen, ***kwargs*)
A _Simulation object to create a Naive Monte Carlo simulation of a Random Walk, with each step being i.i.d. given the _RandomGen RV Generator class

simulate(*periods_forward*, *number_of_simulations*)
Function to simulate each independent walk in the Monte Carlo simulation

Parameters

- **periods_forward** – int, how many steps into the future each random simulated random walk will take

- **number_of_simulations** – int, how many separate independent paths will be simulated

Returns np.array of shape (periods_forward, number_of_simulations), each row is an independent simulation, each column is a time period step

CHAPTER

SEVEN

SOFTWARE LICENSE

CHAPTER

EIGHT

INDICES AND TABLES

- genindex
- modindex
- search

PYTHON MODULE INDEX

r

INDEX

Symbols

A

C

D

E

G

H

M

N

P

Q

R

S

V