The rules of the "game": You choose one of the topics below and write a report (15-20 pages) addressing all the issues of your chosen topic.

Send/upload your report, input data, and code (if any). Submit your response by **latest Friday** 17^{th} **May 2024, 23:59**.

The maximum grade can be achieved with a score of 100 points. Best of luck!

Topics

1) **Borrow/Lending risk assessment** (100 [+ 30 bonus] points)
According to the description in Aave Document Hub, Aave is a decentralized non-custodial liquidity protocol where users can participate as depositors or borrowers. Depositors provide liquidity to the market to earn a passive income, while borrowers are able to borrow in an overcollateralized (perpetually) or undercollateralized (one-block liquidity) fashion.

   The aim of your report is to provide a thorough market risk assessment of the protocol, and in particular to examine the following points:

   i) **(20 points)** Leveraging historical data for cryptocurrencies, assess the appropriateness of the max Loan-to-Value (LTV) figures for collateral being: i) WETH, ii) WBTC, iii) AAVE, or iv) 1INCH while borrowing USDC - latest values can be found in here. The LTV ratio defines the maximum amount of assets that can be borrowed with a specific collateral.

   ii) **(20 points)** Using the historical data assess the appropriateness of the liquidation thresholds for the above collateral cases vs. the LTVs. The liquidation threshold is the percentage at which a position is defined as undercollateralised.

   iii) **(20 points)** Comment on whether liquidators, who are purchasing the collateral as part of the liquidation of a loan, can run a profitable strategy with the defined values of the liquidation penalty for the above collateral options. According to the Aave documentation, the liquidation penalty is a fee rendered on the price of assets of the collateral when liquidators purchase it as part of the liquidation of a loan that has passed the liquidation threshold. Please comment across the following dimensions: i) the size of loan/collateral purchased vs. traded volume of collateral in the "market" (a main centralized exchange or a DEX), and ii) the potential gap risk, i.e. the risk of the purchased collateral price moving sharply down with little or no trading in between, the liquidator might face. How such a gap risk can be priced by the liquidator?

   iv) **(20 points)** Build a simulation framework to stress test the appropriateness of the LTV and liquidation thresholds. Use stochastic paths for the underlying price of the collateral and document your results. Perform your simulations with: i) a Geometric Brownian Motion, and ii) a Geometric Brownian Motion with jumps - calibrate the model on historical data; on a rolling window of choice or any other choice you deem appropriate. Please perform the analysis assuming that a single asset collateral only is provided by the user to borrow USDC.

   v) **(20 points)** Perform simulations on a multi-asset collateral manner with the above stochastic models and assess the appropriateness of the Liquidation Threshold as this is defined in docs.aave and an equally weighted contribution of collateral across the above 4 coins. Stress test the correlation assumptions and document your results.

   vi) **(30 points) bonus item:** Assume an enhancement of the protocol being that the user is given the possibility to leverage a dynamic rebalancing of the collateral provided. The aim of such rebalancing is to manage the overall volatility of the collateral pool by reallocating the weights among the above 4 risky collaterals *and USDC*. This would lead to a smooth and sequential liquidation of risky collateral as opposed to a full liquidation as in the current case of the Aave protocol. Leverage your knowledge on portfolio allocation and define how such a dynamic rebalancing feature would work and, if possible, show case with either simulation or historical data.

2) **Synthetic stablecoin risk assessment** (100 [+ 30 bonus] points) During the lectures we have discussed various forms of stablecoins, such as USDC, USDT, etc. We have analyzed stablecoins which are backed by real world assets, e.g. T-bills, deposits, money market certificates, as well as synthetic stablecoins. An example for the latter is Ethena - USDe. According to the documentation, Ethena provides a crypto-native solution for money that does not rely on the traditional banking system infrastructure, alongside a globally accessible dollar-denominated savings instrument - the "Internet Bond".

   Ethena's USDe is a delta-neutral synthetic dollar that holds collateral outside the traditional banking system. The original idea of the synthetic replication of 1 USD can be found here.

   i) **(10 points)** Describe the source of yield for staked USDe, i.e. the Internet Bond, which drives the return provided to deposited/staked USDe with the protocol.

   ii) **(20 points)** Having identified the source of yield, use historical data and provide summary statistics for the components of that yield across time. Comment on the characteristics of these components and, in particular, their time-varying nature.

   iii) **(10 points)** Provide a qualitative assessment of situations where the deposit to the protocol could actually yield a negative return; which are the stress cases that could lead to such a case.

   iv) **(20 points)** Discuss the implications of a de-pegging event, such as the one of stETH vs ETH exhibited between May 2022 and September 2022 (see here), to the yield as well as to the USDe peg 1:1 to USD. Elaborate on which events could put capital at risk.

   v) **(20 points)** Build a toy-model to calculate how long it would take for the insurance fund to run out of money if perpetuals had persistently negative funding rates.

   vi) **(20 points)** Arbitrageurs typically help to maintain fair values across venues and coin pairs. Describe various ways that an arbitrageur might exploit such arbitrage opportunities when USDe deviates from the 1:1 peg to USD - see times series here.

   vii) **(30 points) bonus item:** Implement the above with historical data and describe the summary statistics of your trading strategy.

3) **Crypto carry** (100 [+ 50 bonus] points)

   Carry trading strategy has been very well analyzed and documented. A carry trade is going long in the spot market, while selling the same amount forward via a futures contract. BIS has recently published a thorough analysis of the carry trade in crypto - see BIS working paper, No 1087. The BIS paper focuses on the carry trade based on 1-month and 3-month futures contracts.

   i) **(20 points)** Instead of fixed maturity contracts, define the framework for executing the carry trade leveraging the so-called "perpetual futures" instead. Describe how perpetual futures work, and how one can build a carry trade in crypto such as BTC and ETH.

   ii) **(50 points)** Use historical data to implement such a strategy and document the results. Use either coin settled or USD (stablecoin, e.g. Tether) settled perpetuals to implement the strategy, or both (and document if any differences in the summary statistics).

   iii) **(30 points)** Provide summary statistics across market corrections and recoveries, similarly to what we have done during the last guest talk we had in the lectures. You can use historical events such as i) the Luna collapse, ii) the FTX collapse, iii) the 2021 bull run or the recent iv) positive momentum after the BTC ETF approval.

   iv) **(50 points) bonus item:** Since perpetual futures are being traded in different venues, analyze how your carry trade summary statistics change across the different venues. Is it worth exploring the implementation of such a strategy across different venues by changing the venue for the short futures position over time? Provide either quantitative evidence or qualitative commentary on your approach.

4) **Advanced Portfolio Construction** (100 [+ 30 bonus] points)

During the lectures we have discussed the crypto data series characteristics and in particular the high correlation exhibited between cryptocurrencies. This has certain implications in portfolio construction and diversification which can achieved in crypto portfolios.

You will be given the following dataset:

Linear returns over date range 02-Oct-2017 to 15-Mar-2024 for the following assets:

- 10 Crypto-USD pairs
- 4 traditional reference asset indices: i) S&P500 (SPXT), ii) Nasdaq (XCMP), iii)USD Overnight Index Swap Rate (USSOC), and iv) VIX Index
- Key dates for conditioning: Previous peak : trough : recovery of "SBF" crash: 11-Sep-2021 (called here: "datePP") to 21-Nov-2022 ("dateTr") to 07-Mar-2024 ("dateRec")
- Data sources: Cryptocompare API for crypto assets; Bloomberg API for traditional assets
- Assume that all crypto assets have sufficient liquidity to be investable for our purposes and that all traditional reference assets have readily available futures contracts such that the index time series behaviour is representative of the actual investment experience.

References to papers made below can be also made available.

1) **(20 points)** Study the dataset and perform some Exploratory Data Analysis (EDA), to inform the rest of the analysis and to raise potential pitfalls and issues to take into account. Produce some visualizations, including correlation heatmaps, rolling correlations, marginal density plots, a table of descriptive statistics and so on, to gain some intuition for the dataset.

   Among others, consider the following:

   (a) Should one use linear returns or log returns for this analysis? Meucci (2010, Linear and Compound Returns) will offer some helpful insights. Specifically, is there something about the marginal distributions of the crypto assets that suggest a methodological choice?

   (b) Are there any outliers in the data? Did you choose to treat them somehow and why?

   (c) For the equity indices (SPXT and XCMP), it is the total return version of these equity indices that are used. Does this matter i) in general, and ii) for the risk-based portfolio optimizations in the rest of this study?

   (d) For the traditional assets – do you notice the zero returns over weekends, when the crypto assets still have returns? Is this a problem (perhaps for estimating correlations etc.) and if so, what do you suggest to do about it?

2) **(30 points)** Address the following:

   (a) Create an equally weighed (EW) portfolio of all 14 assets in the grid, as at i) the previous peak date, datePP: 11-Sep-2021, and at ii) the trough date, dateTr: 21-Nov-2022.

   (b) Create sample covariance matrices at each date (datePP; dateTr) for use in estimation and consider: How much data do you need? (Lopez De Prado, 2016 contains a useful expression). State the size of your chosen data window and justify.

   (c) Now clean the covariance matrix (this may need decomposition into correlations and volatilities) using the eigenvalues clipping method (method no 3), as in Bouchaud et al. (2016). Compare and contrast the raw sample covariance matrix with the cleaned version: create helpful 3D visualizations, kernel density plots of their respective eigen-spectra, and contrast their respective condition numbers: what do you notice?

   (d) Create Euler risk contribution structures for both portfolios at their respective solution dates, for both the raw sample and the cleaned covariances (four in total). Compare these across time and across estimators and note your findings. Can you condense the information from the Euler risk contribution structure into a single number (e.g. by using the Herfindahl index of the risk contributions)?

(e) Create a diversification distribution of the portfolios, following the method in Meucci (2009), and summarize this information as the Effective Number of Bets. Compare this diversification distribution to the Euler risk contributions from d) and compare their respective index numbers – what do you notice?

(f) At the trough date, dateTr: 21-Nov-2022, your EW portfolio will likely have suffered some losses. Create a rank order of these and compare this to the rank order of risk contributions estimated in d), using a visual representation and a rank order correlation matrix such as Kendall's Tau. What do you notice?

3) **(30 points)** Risk-based portfolios:

(a) Using your favourite covariance matrix estimator from Question 2), create the following portfolios, both at datePP as well as at dateTr, under basic non-negativity constraints $w_i \geq 0, \forall i$, and full allocation and leverage constraints $1^{'}w = 1$:

i. The minimum variance portfolio,

ii. The equal risk contribution portfolio (see Roncalli, 2009),

iii. The minimum effective number of bets portfolio of Meucci (2009),

iv. The hierarchical risk parity portfolio of Lopez De Prado (2016).

(b) Compare and contrast their optimal weights across dates and among each other (six portfolios in total). Report your findings and relate this to the risk contribution analysis in Question 2). How comfortable are you in holding these portfolios at their optimal weights? Did your optimization require the use of weight constraints other than the non-negativity and leverage constraint?

4) **(20 [+ 30 bonus] points)** Extensions to Hierarchical Risk Parity:

So far, our primary object for encoding of the dependence information is the correlation matrix. The HRP optimization of Lopez De Prado (2016) offers a framework for generalizing beyond this. When we consider the warning on correlations expressed in Embrechts, McNeil and Straumann (1999), Correlation Pitfalls and Alternatives, it appears both critical and productive to search in the direction of generalizing our measure of dependence.

(a) Consider the distance matrix, D, defined in Lopez De Prado (2016, p.5). This measure is still based on the correlation matrix. Now, Embrechts, McNeil, Straumann (1999) in Correlation and dependency in risk management, properties and pitfalls, express alternative distance metrics (page 17, a la, Schweizer and Wolf, 1981), that may be able to capture additional dependence information and be used in the HRP portfolio optimization context. Build an alternative HRP optimization that uses one of these distances for the distance matrix D.

(b) Solve your new portfolio for both dates, datePP and dateTr and compare the weights the those in the Question 3a) and discuss any interesting findings.