GROUP WORK PROJECT # 3
GROUP NUMBER: 5747

MScFE 652: PORTFOLIO MANAGEMENT

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Remember: Any group members who did **not contribute to the project should be given all zero (0) points for the collaboration grade on the GWP submission page.*

Statement of integrity: By typing the names of all group members in the text boxes below, you confirm that the assignment submitted is original work produced by the group (excluding any non-contributing members identified with an "X" above).	
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INTRODUCTION:

Project 3 is the continuation of project 2 where the best portfolio was selected in terms of the risk reward performance.Portfolio for the student B was the best portfolio under the MVO,Black Litterman Model and Kelly Criteria from project 2. For the purpose of project three,due to the limitations of MVO,BL and Kelly Criteria,the new strategy that attempted to bring the improvement such as denoising,clustering and backtesting were implemented.Each improvement was analyzed from different performance metrics such portfolio return,portfolio risk,sharpe ratio,sortino ratio,conditional value at risk and there were also simultaneous use different improvements to evaluate the portfolio performance.In conclusion the in sample and out sample portfolio performance was analyzed.

STEP 1:

IMPROVEMENTS USING DENOISING:

Denoising techniques are important in improving the accuracy and reliability of the models by removing the meaningful signals from noise. Mostly the estimation errors are mentioned as noise. There are various denoising methods. De Prado also introduced methods to improve the quality of data using denoising.

FEATURES:

- Denoising techniques are very useful and robust against errors and outliers.
- The Principal Component Analysis (PCA) is a denoising method that helps in decomposing the covariance matrix and also isolates the principal components. The principal components are actually the meaningful signals. By focusing on the principal components, PCA reduces the dimensionality and filters out the noise. This improves the data quality and thus lowers the amount of data without losing much of the information.
- Denoising helps in replacing the eigenvalues of the eigenvectors classified as random by Marcenko-Pastur with a constant eigenvalue[1]. This helps in reducing the noise present in the correlation matrix. The important signals are kept while the noise is removed.
- Random Matrix Theory (RMT) with Marcenko-Pastur distribution (MPD), helps in finding the difference between signal and noise in the eigenvalues of the covariance matrix. This helps in finding the non-random eigenvalues.
- Constant Residual Eigenvalue Method (CREM) reduces noise by replacing the noisy eigenvalues with their mean. This helps in getting a more stable covariance matrix for portfolio optimization.
- By introducing a shrinkage coefficient, Targeted shrinkage can be used for the adjustment of the denoising degree. This method allows control of noise reduction and in keeping the important signals. It reduces noise and gives optimal model performance. Targeted shrinkage and CREM are introduced by De Prado.
- MIC-EMD is an adaptive denoising method that can help in removing the noise present in input features. This is done based on the nonlinear relationship between the target variable and the input features[2].

BENEFITS:

- The denoising process reduces the noise in the covariance matrix. This helps in getting more accurate portfolio optimization. This improves the risk-return ratio of the portfolios.
- This helps in finding and keeping the principal components that represent the important signals. Thus helping to make better investment decisions.
- Denoising helps in preventing overfitting by removing the noisy components.
- The noise reduction process decreases the estimation error in the covariance matrix.
- With the targeted shrinkage method, the degree of denoising can be adjusted.
- In a variance-covariance matrix after denoising, we can find the uncorrelated assets easily. This helps in getting a more effective diversified portfolio and in reducing the overall portfolio risk.
- Denoising helps in reducing risk and increasing the returns. Portfolio risk can be found more accurately. The accuracy of the model can also be increased.
- Denoising helps in reducing the importance of non-stationary.
- It also helps in portfolio optimization by finding the optimal asset allocation.
- Stable portfolio performance can be achieved due to denoising.

IMPROVEMENTS USING CLUSTERING:

Based on the similarity, assets are organized into groups. This is called clustering. To make portfolios more diversified and manage risk, clustering can be used.

FEATURES:

- Assets can be grouped based on similarity. These similar characteristics include volatility, performance or market cap and several others.
- Clustering is an unsupervised learning method.
- To measure the similarity between assets, different distance metrics can be used. Some of the common distance metrics are correlation distances and Euclidean distances. A distance metric must satisfy the three conditions: non-negativity, symmetry, and the triangle inequality.
- Hierarchical Clustering arranges assets into a hierarchy. Hierarchical Risk Parity (HRP) is risk parity with hierarchical clustering. This can improve portfolio optimization.
- Gaussian Mixture Model is also a clustering method that forms groups by using mean and variance.
- Clustering can handle large datasets easily.
- K-means algorithm can also be used for clustering.

BENEFITS:

- Grouping the assets with similar risk together, clustering can help in managing the risk.
- Using Hierarchical Clustering, the clustered portfolio gives higher risk-adjusted returns, better standard deviation rates, and improved Sharpe-ratios.
- This method also helps in increasing the robustness of the model.
- Because of the grouping of similar assets, diversified portfolios can be made. Diversification reduces the importance of individual asset volatility on the overall portfolio.

- Mutual Information helps in finding the reduction of the uncertainty. Clustering helps in finding both the linear and non-linear relationships between assets.
- Hierarchical Risk Parity helps in reducing the noise in the data. This helps in getting a more stable portfolio performance.
- For finding the best optimal asset allocation, clustering can be done by grouping assets based on different characteristics. This helps in risk management.

IMPROVEMENTS USING BACKTESTING:

Backtesting is a method, which helps in finding the performance of models. This is used in portfolio management. We can do this backtesting by simulating how a strategy would have performed in the past. This helps in finding the gains and losses of the strategy.

FEATURES:

- Backtesting can be done by finding the accuracy of the predictions we got in the model. Mean Squared Error (MSE) is one of the metrics.
- These metrics help in finding how much the model's predictions are different from the actual historical data.
- Sharpe Ratio is also one of the backtesting methods. This has both return and risk. The performance of the strategy used in backtesting depending on risk can be calculated with this.
- Value at risk is also one of the backtesting methods.
- Walk-forward backtesting helps in testing the model on out-of-sample periods. This method helps in finding the robustness of the model. This can also help in finding if the strategy can be used during different market conditions.
- Cross-validation backtesting uses k-fold cross-validation. This method also helps in finding the robustness of the model.

BENEFITS:

- Backtesting helps in finding if the model is overfitting or underfitting. On unseen data, the model is tested to find the performance.
- In backtesting, the historical data is used to check the strategy performance.
- The robustness of the model can be found during backtesting.
- During backtesting, the risk of the model can be found using the risk metrics. This can help in risk management.
- The potential risks can be found during the backtesting and then we can reduce the risk of the strategy.
- The model's hyperparameters can be fine-tuned during backtesting. This can help in improving the performance of the strategy.
- The backtesting helps in finding if the strategy can be used or not.
- During backtesting, by checking on the performance of strategy, we can find where the model performs better and the strategy's weakness.

- During different market conditions, if the strategy can be used or not is found during the backtesting.
- During backtesting, we can find the parameters that need to be optimized to improve the performance of strategy.
- The risk-reward ratio can be found during this and thus we can help the strategy have a better risk-reward ratio.

STEP 2:

Market capitalization data of S&P 500 tickers are fetched. For the top 100 companies based on market capitalization, 3 different portfolios are created. For the best portfolio of GWP2, we have chosen the MVO portfolio. Mean-variance optimization is done for the three portfolios to find the optimal weights. Each portfolio's mean return, standard deviation, sharpe ratio, variance, expected shortfall (CVar), maximum drawdown and sortino ratio are also calculated. Portfolio B is the best in terms of risk and reward. It offers the highest mean return, the lowest standard deviation, and the highest Sharpe and Sortino Ratios. It also has the lowest expected shortfall, variance, and maximum drawdown, making it the most favorable portfolio when balancing risk and reward.

Improvements using denoising:

Principal Component Analysis (PCA) is done to reduce noise in the portfolio. Then the denoised data is used for MVO. The result obtained is the after denoising results.

STUDENT B	BEFORE DENOISING	AFTER DENOISING
MEAN RETURN	0.00051	0.00053
STANDARD DEVIATION	0.00803	0.00739
SHARPE RATIO	0.06378	0.07175
EXPECTED SHORTFALL (CVar)	0.01791	-0.01906
VARIANCE	6.45137e-05	5.46441e-05
MAXIMUM DRAWDOWN	-0.12803	-0.03401
SORTINO RATIO	0.09260	0.09217

Table 1: Results before and after denoising

The improvement based on denoising improved the portfolio return,portfolio risk,sharpe ratio,maximum drawdown while there were no changes on the sortino ratio.The cVar became

negative that required further analysis.The denoising improved the portfolio allocation in such that it increases the portfolio returns and minimize the portfolio risk therefore recommended and useful when the portfolio allocation is done in practice.The reason that made the cVaR negative is unknown.It could be because of the market volatility or the nature of the dataset with some extreme cases.

We are noticing some changes in the performance metrics after applying the denoising procedure. There is a change upwards in the mean return that goes from 0.00051 to 0.00053 and this can be classified as a small improvement. The standard deviation goes down from 0.0080 to 0.0073 which means that the portfolio risk has been lowered. Talking about risk we are noticing improvement in the Sharpe ration that goes from 0.0637 to 0.0717.
Meanwhile the Cvar turned negative from 0.0179 to -0.01906 after the denoising. We consider this as a strange phenomenon that would be interesting for some further investigation. Otherwise, the variance decreases from 6.4513708448e-05 to 5.4644084192e-05 which again suggests lowering the overall risk.
The measure of potential losses named maximum drawdown also decreases from 0.128 to 0.034. This is also good for lowering overall risk. The Sortino ratio goes from 0.0926 to 0.0921 which means that there is no considerable risk-adjusted returns improvement. We can conclude that after denoising we reach the following improvements: improved mean return, reduced standard deviation, and enhanced Sharpe Ratio. We should also point out that the unexpected negative CvaR need further experiments and investigation

Improvements using Clustering:
Using K-means, assets are grouped into 5 clusters. For each cluster, MVO was done. This helps in a diversified portfolio. The clustered weights are combined into a final portfolio. The optimal weights, portfolio mean return and standard deviation are calculated.

STUDENT B	AFTER CLUSTERING
MEAN RETURN	0.00051
STANDARD DEVIATION	0.00803
SHARPE RATIO	0.06378
EXPECTED SHORTFALL (CVar)	0.01791
VARIANCE	6.45137e-05
MAXIMUM DRAWDOWN	-0.12803
SORTINO RATIO	0.09260

Table 2: Results after clustering

The k-means clustering was implemented and the following results were found on the portfolio metrics.In overall,there were no significant improvements that clustering brought except sortino ratio,meaning the downside risk was better than the MVO portfolio.

After the clustering we may compare the results and we see that after the clustering we get these results for the specific metrics: Mean Return = 0.0005, Standard Deviation = 0.00803, Sharpe Ratio = 0.0637, Expected Shortfall (CVaR) = 0.0179, Variance = 6.451370840918194e-05, Maximum Drawdown = -0.128, and Sortino Ratio = 0.0926.
Comparing with the portfolio before the clustering that had the following values for the specific metrics: Mean Return = 0.0005, Standard Deviation = 0.00803, Sharpe Ratio = 0.0637, Expected Shortfall (CVaR) = 0.0179, Variance of 6.451370844789015e-05, and Maximum Drawdown = -0.12803
After comparing these results we cannot say that there is significant difference in mean return, standard deviation, Sharpe Ratio, Expected Shortfall (CVaR), Variance, and Maximum Drawdown between the two portfolios. The difference is in the improvement of the Sortino ratio which means that there is better performance measured in the downside risk.

Improvements using Backtesting:
Mean-variance optimization is done for the portfolio. Mean return, standard deviation, sharpe ratio, variance, expected shortfall (CVar), maximum drawdown and sortino ratio are calculated for Student B's portfolio. These are calculated to check the performance of portfolios. Optimal weights are also calculated.

STUDENT B	AFTER BACKTESTING
MEAN RETURN	0.00051
STANDARD DEVIATION	0.00803
SHARPE RATIO	0.06378
EXPECTED SHORTFALL (CVar)	0.01791
VARIANCE	6.45137e-05
MAXIMUM DRAWDOWN	-0.12803
SORTINO RATIO	0.09260

Table 3: Results after backtesting

On the backtesting,the combinational purged cross-validation method was implemented to address overfitting.The portfolio return and sharpe ratio improved while other metrics did not improve at all.

We can see that the volatility of all the portfolios are much better than after clustering. We can also see the cumulative returns percentage. The sharpe ratio implies the return/risk relationship. This helps in knowing the risk-reward relationship.

We are fighting overfitting by applying the Combinatorial Purged Cross-Validation (CPCV) method. This is how we can make a better evaluation of the portfolio performance by using many combinations of training and testing datasets. We see the following improvement afterwards the CPCV: mean return increase from 0.00051 to 0.00095 which is an enormous improvement. We can say that this is how we managed to almost double the mean returns. The standard deviation went from 0.00803 to 0.01184, which means that the portfolio volatility has increased as well as the mean returns. This should be normal, because with greater risk come greater opportunities and potential profits so all is good. The Sharpe Ratio also improved from 0.0637 to 0.0811. The variance increased from 6.451375359356243e-05 to 0.00014 which is expected because of the bigger standard deviation. The Sortino ratio decreased a bit from 0.0926 to 0.0835 and thus we can say that we are achieving lower risk-adjusted returns. We should also add that CvaR turned negative from 0.0179 to -0.0249 and this means that we can expect some bigger short-term losses. Consequently, the maximal drawdown got a bit worse from -0.128 to -0.173. Overall CPCV did improve the metrics, but it brings bigger risk to the portfolio as well. We can say that the risk-adjusted return improved with some bigger volatility that brings bigger risk as well

STEP 3:
Improvements using denoising and clustering:

STUDENT B	AFTER DENOISING AND CLUSTERING
MEAN RETURN	0.00053
STANDARD DEVIATION	0.00739
SHARPE RATIO	0.07154
EXPECTED SHORTFALL (CVar)	-0.01906
VARIANCE	5.46441e-05
MAXIMUM DRAWDOWN	-0.03401
SORTINO RATIO	0.09217

Table 4: Results after combined denoising and clustering

We decided to implement both denoising and clustering at the same time to achieve even better results for the performance metrics. The mean return of the portfolio increased from 0.00051 to 0.00053 which is welcome. The Standard deviation decreased from 0.00803 to 0.00739 which is a noticeable portfolio risk (volatility) reduction. Also, the Sharpe Ratio improved from 0.0637 to 0.7175 and thus we archived better returns for every unit of risk. In other words, said: the risk-adjusted return of the portfolio improved.

Notably, the Expected Shortfall (CVaR) exhibited a significant improvement, decreasing from 0.0179 to -0.019. We decided to implement both denoising and clustering at the same time to achieve even better results for the performance metrics. The mean return of the portfolio increased from 0.00051 to 0.00053 which is welcome. The Standard deviation decreased from 0.00803 to 0.00739 which is a noticeable portfolio risk (volatility) reduction. Also, the Sharpe Ratio improved from 0.0637 to 0.7175 and thus we achieved better returns for every unit of risk. In other words, said: the risk-adjusted return of the portfolio improved.

Lowering the CvaR is a good achievement because this means that we are potentially lowering the expected future losses if the worst-case scenario materializes, and we happen to have a sequence of conditional losses. The portfolio variance went down from 6.451370844789015e-05 to 5.464408419176055e-05. Also, the maximal drawdown decreased from -0.128 to -0.034 and this can be interpreted as: smaller losses during the price action and the given market conditions.

We must admit that the Sortino ratio stayed flat at 0.0921but this is what it is. It would be even better for it to go lower as well, but as I said: it is what it is.

In conclusion we can say that this approach gave improved returns and reduced risk metrics, which is the main goal of doing all these exercises. So we are glad for the results that we achieved.

STEP 4:

The in-sample portfolio that is being tested has a mean return of 0.016% and a standard deviation of 1.13%. Its Sharpe Ratio is 0.0149 and the Sortino ratio is 0.0147. The Cvar is -2.66% which means that in the short term there may be expected some consecutive losses. The drawdown is -15.69% with portfolio variance of 0.0129%

Now about the out-of-sample portfolio: it shows improvements in the corresponding metrics like mean return goes up to 0.2057%, which is better for the given period. The standard deviation decreases to 1.02% and this could be said as: this portfolio has a lower volatility (which is good). The Sharpe Ratio (0.2022) and Sortino Ratio (0.1853) are better compared to the in-sample portfolio and both Value at Risk (VaR) and Maximum Drawdown are decreasing which suggests lower risk and better performance.

We could say that our out-of-sample portfolio is the better one compared to the in-sample one. With its higher returns, lower volatility (i.e. risk) and improvement in risk-adjusted returns, we are beating the in-sample results. Although we are getting this good result there is no guarantee that things will stay this way forever and this is why we should do constant improvements and monitoring of these metrics. (I guess this is the job of the Portfolio Manager after all)

STEP 5:

PERFORMANCE DIFFERENCE:

We did a lot of improvements that lead to better results like mean return, standard deviation, Sharpe Ratio, Sortino Ratio, Value at Risk (VaR), Maximum Drawdown, and Expected Shortfall (CVaR). We noticed great benefit from the combination of clustering, denoising and cross validation methods, especially the combinatorial purged cross validation method for the backtesting.

For example, denoising with PCA lowers the noise (the not so important data) and thus thanks to some linear combinations brings out only the most important data which is called principal components. Then we are working only with the relevant data, which brings down the computational cost and the time consumed respectively. Also, the CPCV method was very useful which helps with cross validating time-series data and thus improves the learning of the dependencies in the data itself.

This is how better mean returns were achieved while having lower volatility and lower risk-adjusted returns.

Considering all the results above and during this experiment we can conclude that: YES, it is worth the additional complexity and effort because overall we are getting much better results and this is the final goal. It would not be worth it if we had not achieved these improvements but since we did so the final conclusion is: Yes, it all worth it.

STEP 6:

ESTIMATION ERROR

Estimation error is the difference between actual parameter and estimated parameter. This is just the difference between the prediction and the true value.

$$err = \underline{\theta} - \theta$$

$\underline{\theta}$ - Estimated value
θ - Actual value

Estimation error can result in lower returns and higher risks.
PCA Denoising done for the students' portfolio helps to reduce the estimation error.

DENOISING WITH PCA (Reduce Estimation error)

Principal Component Analysis or PCA, is a dimensionality reduction method that is often used by transforming large datasets into a set of uncorrelated components called principal components.

Goal:

- Denoising isolates the principal components. By focusing on the principal components, PCA reduces the dimensionality and filters out the noise. Mostly the estimation errors are mentioned as noise.
- To reduce noise and thus estimation error in the input data used for portfolio optimization.

IMPACT OF PCA DENOISING ON ESTIMATION ERROR

STUDENT B	BEFORE DENOISING	AFTER DENOISING
MEAN RETURN	0.00051	0.00053
STANDARD DEVIATION	0.00803	0.00739
SHARPE RATIO	0.06378	0.07175
VARIANCE	6.45137e-05	5.46441e-05
MAXIMUM DRAWDOWN	-0.12803	-0.03401
SORTINO RATIO	0.09260	0.09217

EVALUATING THE EFFECTIVENESS OF PCA DENOISING

After denoising, reduced estimation errors in the covariance matrix lead to more reliable optimal weights.

Metrics After Denoising:
Mean Return:

- More stable and consistent returns.

Standard Deviation:

- Reduced standard deviation, indicating reduced risk.

Sharpe ratio:

- Better risk-adjusted returns.

Variance:

- Less volatility.

Maximum Drawdown:

- Reduced risk of significant loss and improved stability.

Sortino ratio:

- Very slight reduced downside risk.

CONCLUSION:

In this project, for better portfolio management, we have selected the portfolio with the best risk-reward relationship and done improvements like denoising, clustering and backtesting. We have found values for different metrics like mean return, standard deviation, Sharpe Ratio, Sortino Ratio, Value at Risk (VaR), Maximum Drawdown, and Expected Shortfall (CVaR) to find the performance of the model due to these improvements. The experiment of combined improvements was also successful which resulted in better mean returns, lower standard deviation and better risk-adjusted returns.

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