Gold Returns

Capstone Project 2 - Springboard Data Science Career Track

Agenda

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Introduction

Background

In Trading, two main paradigms exist in terms of market analysis:

Fundamental Analysis - This type of analysis focuses on analysing general economic indicators (economic growth, inflation, interest rates, etc), as well as, news events which can affect a particular trading instrument.

Technical Analysis - Technical Analysis, on the other hand, focuses more on trying to identify possible patterns or signals in the data of a particular instrument, in order to predict whether it will go up or down in price.

Technical vs Fundamental Analysis

In academic circles, Technical Analysis is mostly dismissed as being equal to making future predictions based on chance.

However, Andrew Lo, an MIT professor, who initially dismissed Technical Analysis, later published a paper in which he and his co-authors concluded that *“several technical indicators do provide incremental information and may have some practical value.”*

Project Objectives

Analyze, visualize and model Gold return data and try to answer some of the following questions:

- Does the price trend in particular time intervals, such as particular hours, days or months?
- Does the price exhibit any particular patterns repeatedly?

Datasets used

XAUUSD Price Data - This is the main dataset with historical Gold Price data from May 5th, 2003 up to April 30th, 2019

XAGUSD Price Data - This is an additional dataset with historical Silver Price data from August 8th, 2003 up to April 30th, 2019

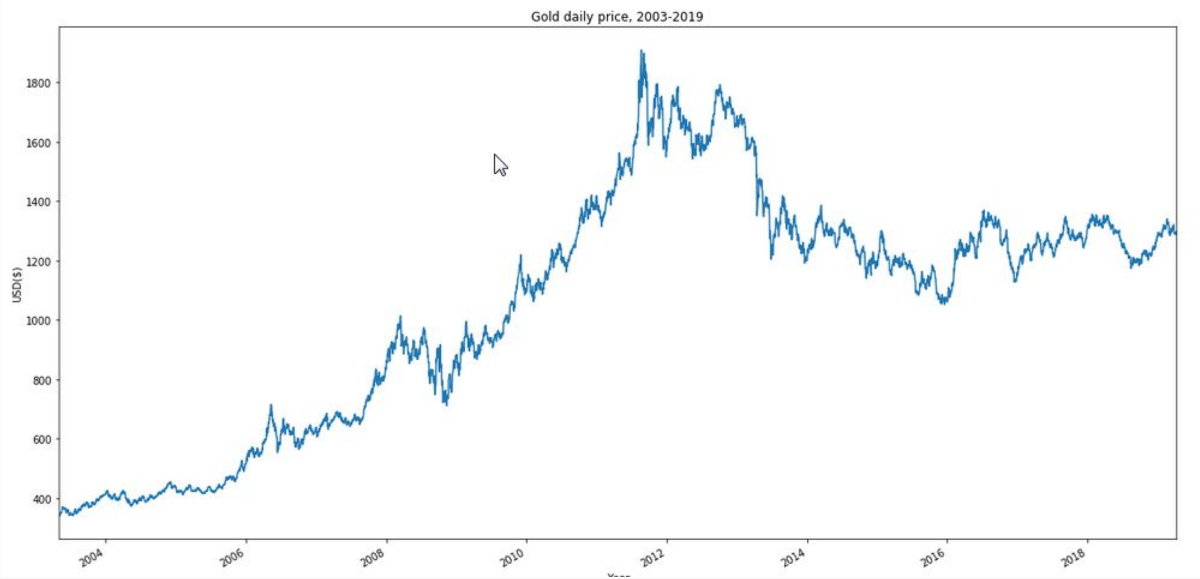
EURUSD Price Data - This is an additional dataset with historical Euro/Dollar exchange rate data from May 5th, 2003 up to April 30th, 2019

Initial Analysis

First steps

The initial analysis of the dataset focused on gathering an overall idea on the trend in the Gold price data.

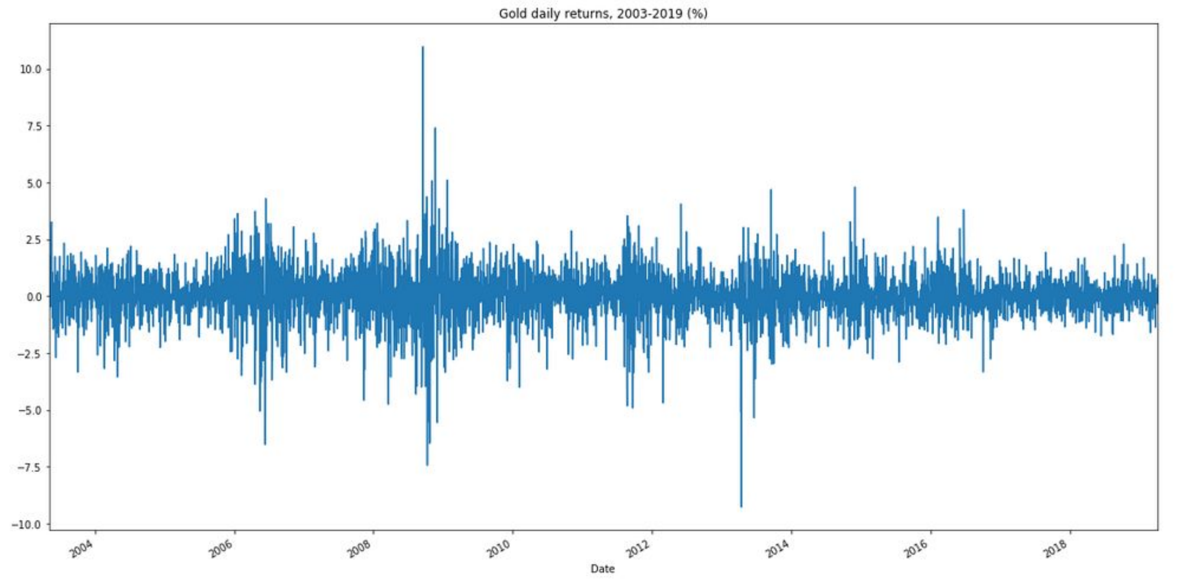
As shown here, the price of gold peaked around 2011, when it reached $1,920/oz.



First steps

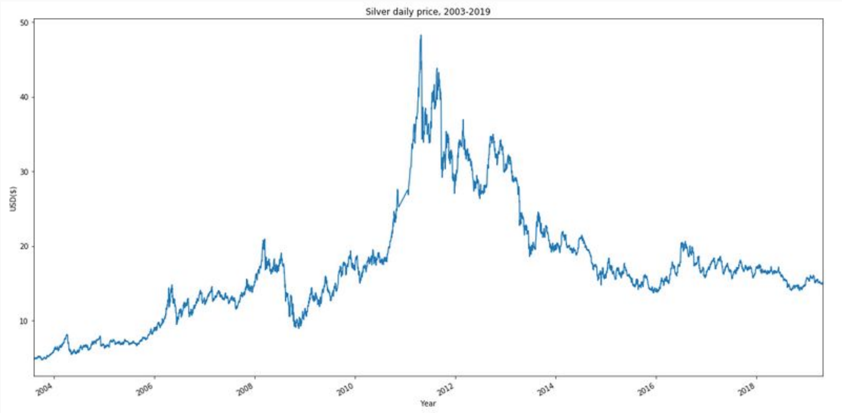
A second step involved looking at the daily return time series, which was derived from price data.

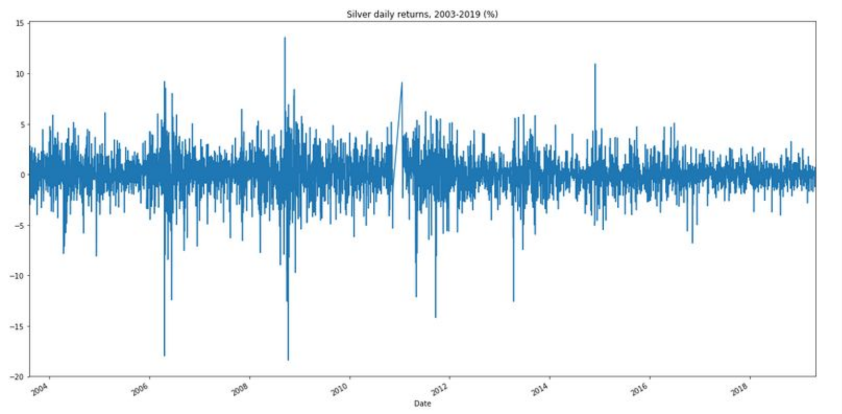
Although Gold price peaked in 2011, its peak return happened in 2008, when the financial crisis began



Silver Data

The same price and daily return plots were also made for both the Silver and Euro data. The silver plots are shown here:

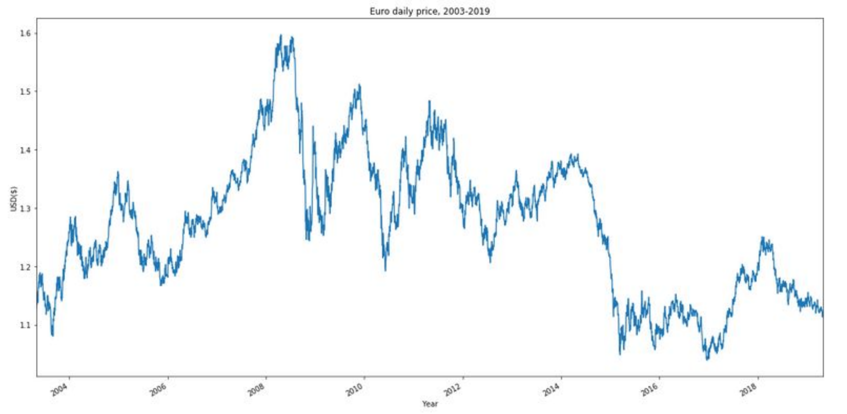


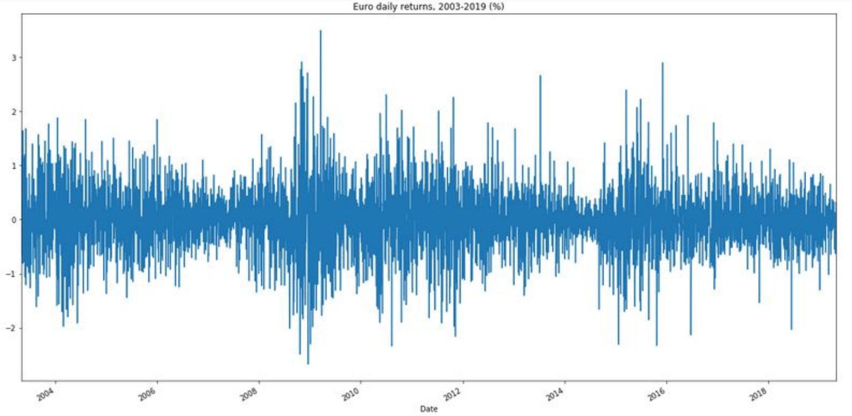


As there is a strong correlation between Gold and Silver prices, Silver peaked also in 2011 due to demand for industrial applications. Also, like Gold, peak returns occurred in 2008.

Euro Data

The following are the plots for the Euro (EUR/USD):





The Euro reached its peak in 2008, as the US entered into recession first. However, in terms of daily returns, the currency is less volatile than both precious metals.

Some initial thoughts

Based on this first analysis, we saw that there is some correlation between Gold prices and Silver and Euro prices.

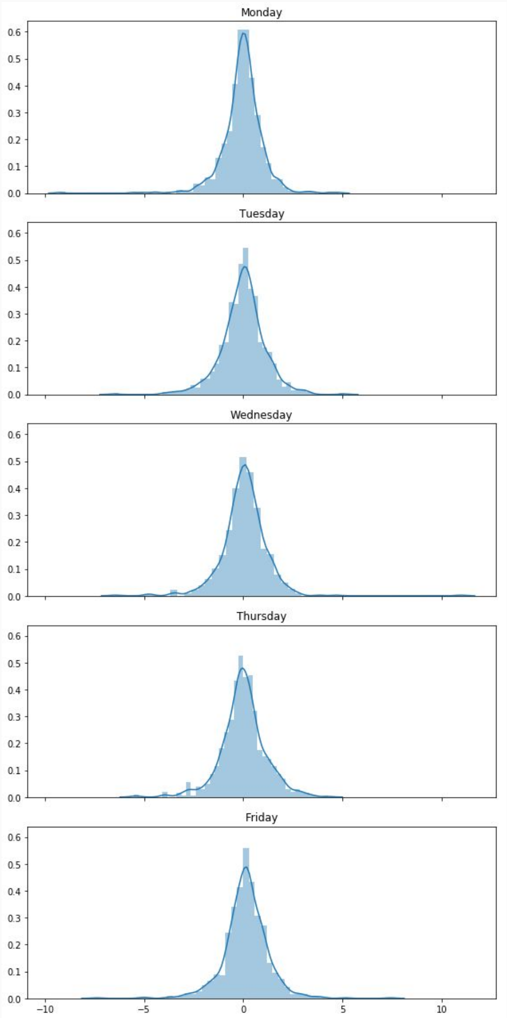
Major economic events such as the beginning of the 2008 economic recession affected these 3 instruments, as they reached peak levels in both price and volatility of their daily returns.

In-depth Analysis

Distribution of Gold daily returns per day of the week

One of the first steps in performing in-depth analysis using inferential statistics was to analyze if there was any sort of difference in daily return distribution according to the day of the week.

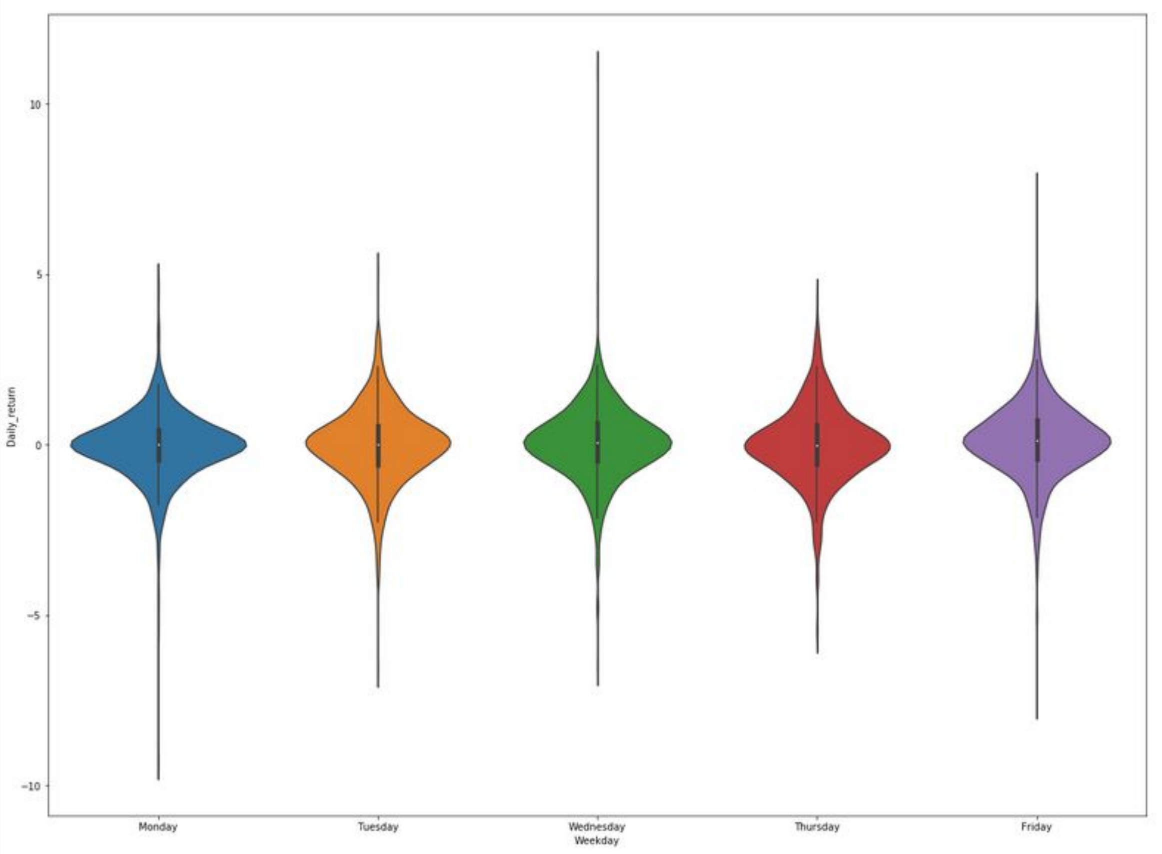
The distribution plots for each day of the week are shown. As we can see, although there is some variation in terms of highs and lows, the returns appeared to follow a normal distribution, regardless of the week day.



Violin plot of daily returns

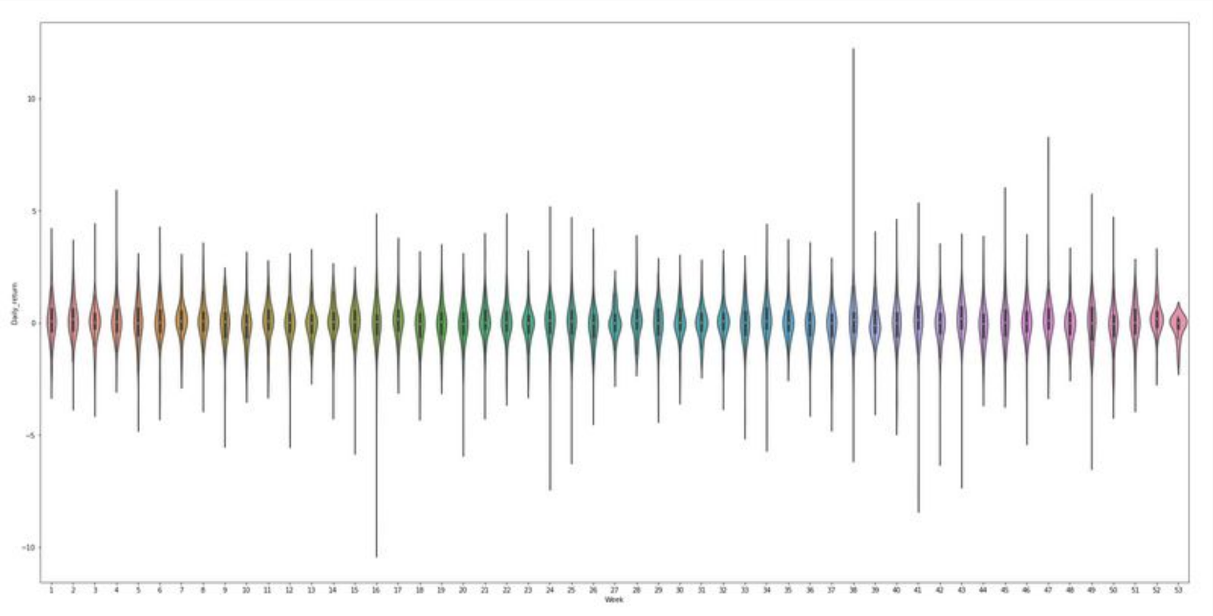
In order to get additional insights on the daily returns, a violin plot helped provide a different perspective.

As we can see, the most volatile days seem to be Wednesdays, Fridays and Mondays, while Tuesdays and Thursdays have smaller range of daily returns.



Daily return distribution by week of the year

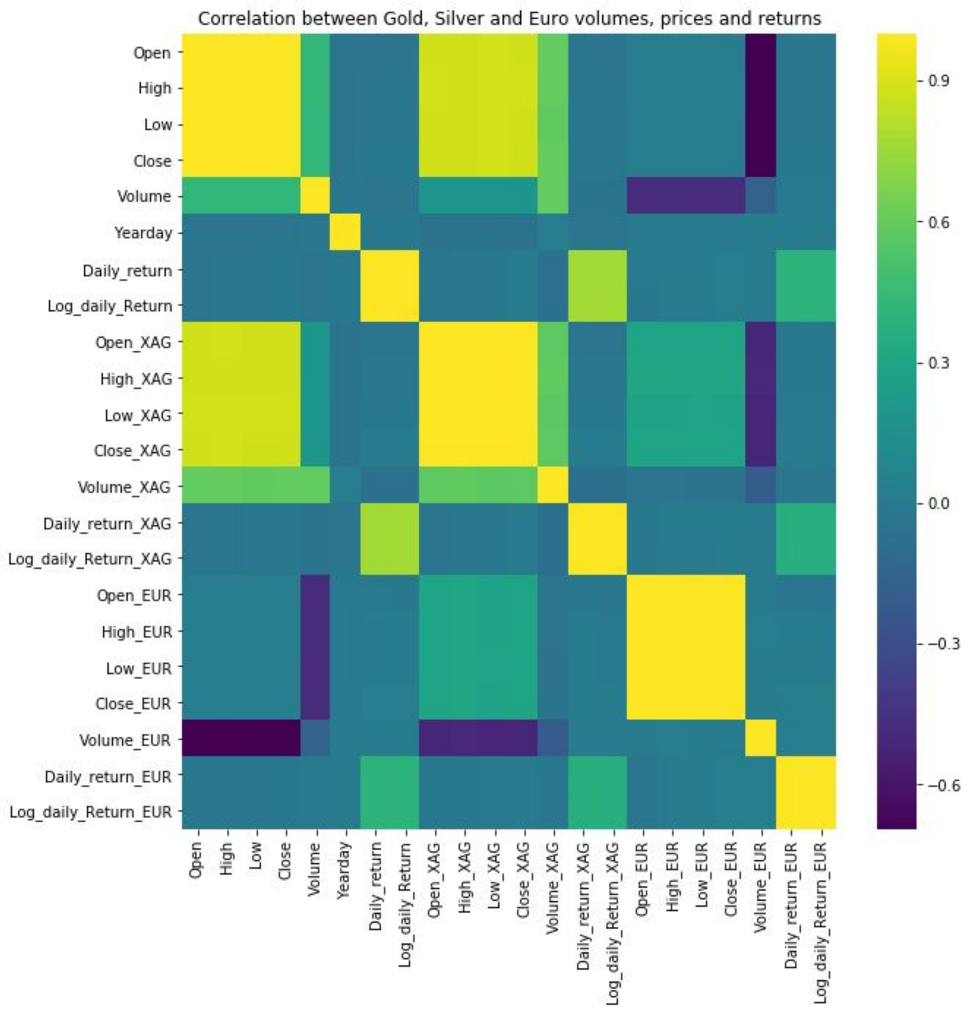
Another perspective was also obtained by grouping and plotting daily returns according to the week of the year. As the plot shows, there is a cyclical patterns, where weeks of high volatility are followed by weeks with less volatility:



Correlation Matrix for prices and returns

As the last step in this analysis, correlation matrices were calculated. The first one was for the correlation between the different prices, volumes and daily returns for the three instruments under study.

This particular correlation matrix confirmed our initial finding of correlation between Gold and Silver prices.

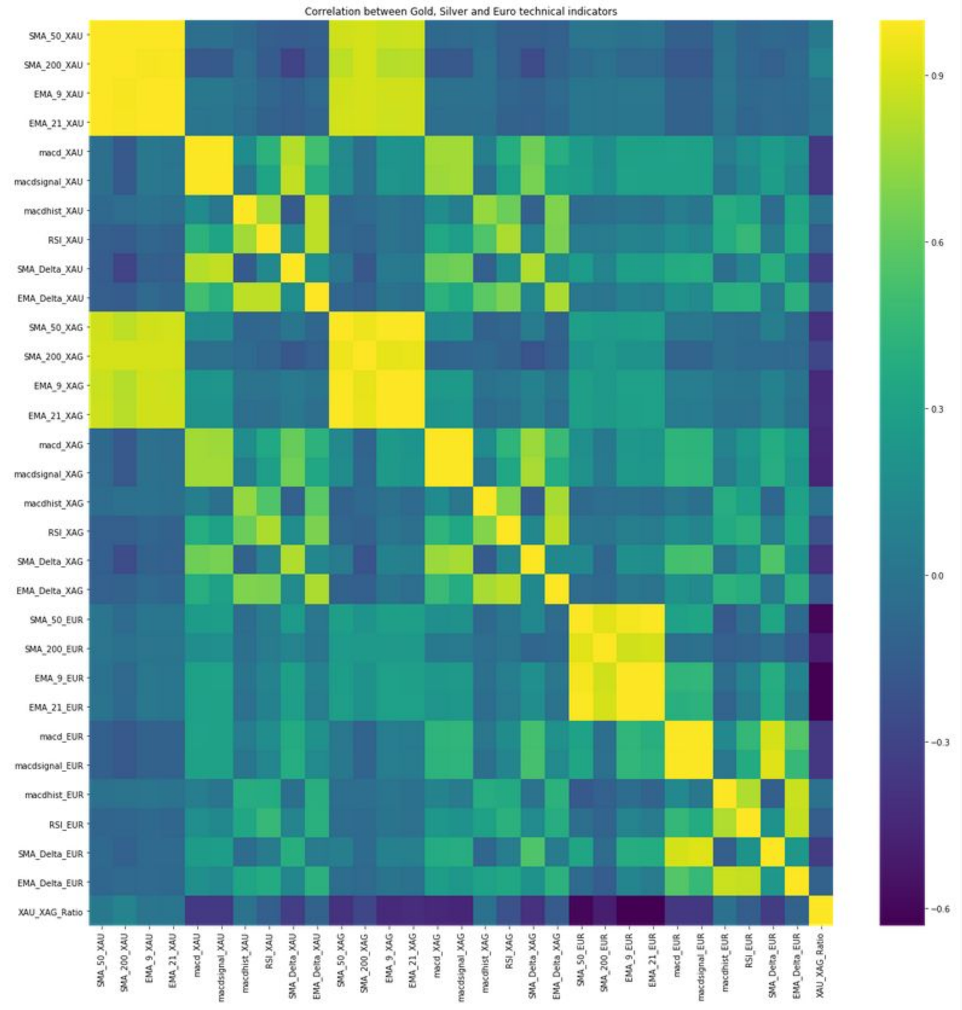


Correlation Matrix for technical indicators

In addition to the price data, we calculated the values of several technical indicators for the 3 instruments.

The technical indicators used were: Simple Moving Average, Exponential Moving Average, Moving Average Convergence Divergence, Relative Strength Index and Gold/Silver ratio.

We see a correlation between Gold and Silver SMA's and EMA's. Also of interest, is the strong negative correlation between the Gold/Silver ratio and the Euro SMA's and EMA's.



Machine Learning & Deep Learning results

Logistic Regression

After performing the initial and in-depth analysis, the project focused on developing some machine learning models in order to predict future daily returns based on historical data.

The first set of models used Logistic Regression, including the use of SMOTE in order to deal with unbalanced data.

Unfortunately, the results with both variations were not good at all, as shown by the result metrics.

	Logistic regression without SMOTE				Logistic regression with SMOTE			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
0	0.56	1	0.71	531	0.36	1	0.53	301
1	0	0	0	424	0	0	0	530
micro avg	0.56	0.56	0.56	955	0.36	0.36	0.36	831
macro avg	0.28	0.5	0.36	955	0.18	0.5	0.27	831
weighted avg	0.31	0.56	0.4	955	0.13	0.36	0.19	831

Random Forest Classifier

The second set of models made use of a Random Forest Classifier.

Given the poor results of using SMOTE, a variation of the model was developed which used price data, in addition to the return data

The results were better than those obtained by Logistic Regression, however, not good enough to warrant their application.

	Random Forest Classifier				Random Forest Classifier (w/ Price Data)			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
0	0.57	0.7	0.63	531	0.56	0.78	0.65	531
1	0.46	0.33	0.38	424	0.47	0.25	0.32	424
micro avg	0.53	0.53	0.53	955	0.56	0.56	0.56	955
macro avg	0.52	0.51	0.5	955	0.53	0.55	0.51	955
weighted avg	0.52	0.53	0.52	955	0.68	0.56	0.6	955

Gradient Boost Classifier

The third set of models used a Gradient Boost Classifier, with returns data only, and another variation using returns and price data.

The results using returns data were slightly better than those obtained by the Random Forest Classifier, however, still not good enough for practical use.

	Gradient Boost Classifier				Gradient Boost Classifier (w/ Price Data)			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
0	0.58	0.71	0.64	531	0.56	0.98	0.71	531
1	0.49	0.35	0.41	424	0.53	0.02	0.04	424
micro avg	0.55	0.55	0.55	955	0.56	0.56	0.56	955
macro avg	0.53	0.53	0.52	955	0.5	0.54	0.38	955
weighted avg	0.54	0.55	0.53	955	0.97	0.56	0.7	955

Machine Learning Models with Gold, Silver and Euro data

While the previous models only used Gold data, a last set of Machine Learning models was developed which combined Gold data with the Silver and Euro data which was described above. The models utilized the same classifiers previously used and the results were as follows:

	Logistic regression (XAG/XAU/EUR)				Random Forest Classifier (XAG/XAU/EUR)				Gradient Boost Classifier (XAG/XAU/EUR)			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
0	0.57	0.68	0.62	524	0.56	0.73	0.64	527	0.57	0.85	0.68	527
1	0.48	0.36	0.41	419	0.46	0.28	0.35	416	0.49	0.18	0.27	416
micro avg	0.54	0.54	0.54	943	0.53	0.53	0.53	943	0.56	0.56	0.56	943
macro avg	0.52	0.52	0.52	943	0.51	0.51	0.49	943	0.53	0.52	0.47	943
weighted avg	0.53	0.54	0.53	943	0.52	0.53	0.51	943	0.53	0.56	0.5	943

Surprisingly, the Logistic Regression proved to be the best model out of the three...

Deep Learning Models

The last steps in our project was to predict daily returns using Neural Networks. The models were developed using Keras and the results were very disappointing, as summarized in the table below:

	Deep Learning				Deep Learning (w/ Price Data)				Deep Learning (XAG/XAU/EUR)			
	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
0	0.56	1	0.71	531	0.56	1	0.71	531	0.56	1	0.72	527
1	0	0	0	424	0	0	0	424	0	0	0	416
micro avg	0.56	0.56	0.56	955	0.56	0.56	0.56	955	0.56	0.56	0.56	943
macro avg	0.28	0.5	0.36	955	0.28	0.5	0.36	955	0.28	0.5	0.36	943
weighted avg	0.31	0.56	0.4	955	0.31	0.56	0.4	955	0.31	0.56	0.4	943

Conclusions

Conclusions

The results obtained by the various algorithms cannot be implemented in real-life, as they did not provide any real predictive accuracy,

However, the skills that I learned from working in this project can certainly be utilized towards any future machine learning and/or deep learning project which I may endeavour to pursue in the future.

In terms of future work with this particular dataset, my research work will continue in terms of combining other data sources, as well as, combining price-prediction models in order to help determine future returns.