A C++ scoring algorithm for ranking global currencies based on financial market sentiment

C++ Programming
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Motivation

Suppose an investor wishes to rank global currencies based on available market information. It would be erroneous to rank those currencies based on their pairwise level. For example, 1 Brazilian Real equalling 35.02 Japanese Yen (as of 06/01/2018) gives no indication of how “strong” the Brazilian Real is compared to the Japanese Yen. If anything, the Japanese Yen should be “stronger” as it is often seen as a safe currency in periods of economic turbulence.

One possible approach for ranking currencies is to assess the volatility skew of the currency pair. One can easily obtain (on Bloomberg for example with the Volatility Surface Function) the market view of the expected volatility skew for a currency pair by quoting its 25-Delta risk reversal, which is the difference of implied volatilities paid or charged on OTM calls versus OTM puts for a given set of options on the currency pair (and given the maturity level). Thus, through quoted 25D risk reversals, we can gauge trader sentiment on the direction a currency pair is headed.

Legend: Legend: AUDUSD (blue) & 25D Risk Reversal AUDUSD (red)

For example, a positive risk reversal for the Japanese Yen/Brazilian Real (JPY/BRL) would indicate that market agents lean more towards a rise in the JPY/BRL currency than a downturn. This would make a decent indicator for assessing whether a currency is “stronger” than another.

Implementation

We fill a square matrix $M \in \mathcal{M}_{n\times n}(\mathbb{R})$ of risk reversal values, where n is the number of currencies. Each row $i \in [\![1,n]\!]$ and column $j \in [\![1,n]\!]$ gives the 25D risk reversal M_{ij} for a currency pair (i,j). As the 25D risk reversal value M_{ji} is simply the opposite $-M_{ij}$ and that there are no values for M_{ii} (which we assume here for convenience is equal to $M_{ii} = 0$), the matrix M is antisymmetric.

To obtain a ranking of currencies, we must compute a score vector $S \in \mathcal{M}_{n\times 1}(\mathbb{R})$ where S_i is the score for a currency i. We set up an outer-difference matrix $O \in \mathcal{M}_{n\times n}(\mathbb{R})$ for this sector vector. To obtain the score vector S, we consider the following minimization objective: $S^* = \underset{S}{\operatorname{argmin}} \ ||M - O||_2^2$. As shown in the appendix, this can be reformulated as a least squares minimization of an overdetermined system of equations. From there, we obtain a ranking of currencies S^*.

We run our algorithm on a real-world snapshot of 25D risk reversal values (1 Week Maturity) from 08/01/2018 on 17 currencies and 2 precious metals (gold, silver). We have to warn however that some of estimates might be biased: on several of the "weaker" currencies (such as the Thai Baht, South African Rand, Russian Rouble or Brazilian Real) paired with precious metals (Gold, Silver), there were no risk reversal data. We make a rather arbitrary assumption that the Gold/Silver – "weaker" currencies pair is equal to the mean of all available Gold/Silver – Currency risk reversal pairs. This shouldn't influence our results as much since they are already the weakest currencies.

We obtain the following results (in descending order from the "strongest" to the "weakest" currency):

Currency	Score (S_i)
Gold (XAU)	0.567956
Silver (XAG)	0.562206
Swiss Franc (CHF)	0.531661
Euro (EUR)	0.399333
Japanese Yen (JPY)	0.37995
Chinese Renminbi (CNY)	0.290411
US Dollar (USD)	0.187278
British Pound (GBP)	0.168128
Hong Kong Dollar (UKD)	0.157778
Danish Krone (DKK)	0.143306
Canadian Dollar (CAD)	0.132082
Australian Dollar (AUD)	0.112983
New Zealand Dollar (NZD)	0.106217
Swedish Krone (SEK)	0.0860667
Norwegian Krone (NOK)	0.00666111
Thai Baht (THB)	-0.0491
Brazilian Real (BRL)	-0.865278
Russian Rouble (RUB)	-1.36694
South African Rand (ZAR)	-1.54273

Data: *Bloomberg Volatility Surface, 1W 25D Risk Reversal values, 08/01/2018*

Interpretation

Several observations can be inferred from the results:

- **The objective of such a manipulation is to assess the current strength of a currency over others**. The main drawback to avoid was to consider only a currency in respect with another one: a pair of currency would have been of no use, as one pair going up could be either a momentum from the first or a weakness from the second. This global ranking takes into consideration the evolution of the main currencies with respect to the others over a fairly short amount of time. The result that comes out of the process is the translation of some currencies expecting to perform better against the majority of the others, over the observed period of time. It is meant to be interpreted as a market view of a market over the FX pairs.

- **The ranking must be seen as an ordinal ranking (in the sense of classical utility theory) since the score of a currency doesn't reflect the currency's macroeconomic fundamentals**.

- **We can also see that precious metals (Gold XAU and Silver XAG) rank highly in our score vector**. This makes sense in the context of the antisymmetric matrix we provided since Gold /Silver risk reversal pairings with other currencies were always positive. They are often seen as safe havens during periods of downturn and remain attractive diversifiers during periods of economic stability.

- **From this ranking, one can infer for example the relative strength of the JPY, CHF and EUR, compared to the BRL, RUB and ZAR over the options' life**. Market sentiment is on for the Japanese and Swiss side – Abenomics is finally working out and Swiss knows best GDP growth quarter since 2014 - as well as for the Euro Area, where the confidence has reached a 20-year high. On the contrary, Brazil's government, still embezzled in corruption affairs, trials and inertia on key reforms to implement has led the currency to drop to a 7-month low, from despair. After a good year, the Ruble is on to face the turmoil a new election: Poutine is foreseen as the next president which is not interpreted as good news for the currency's strength. Besides, Russia is on stage to be hit by US sanctions, worsened by the weaker growth of the last quarter. In a nutshell, all red lights are flickering on the Ruble. As for South Africa, the country has just elected a new ANC leader meant to topple Zuma. The Rand is down because of a strong correction following the euphoria of a renewal at the top of the state. Such economic and political and energy-related news have carried long-term implications over the soundness of the economies and the momentum of investments to come. Given these disheartening news, prospects are dim for the aforementioned economies, which translates on the market by weaker currencies.

Appendix: Least squares implementation

Consider for simplicity that there are only 3 currencies to rank. We have an **antisymmetric matrix** of rank 3, $M \in \mathcal{M}_{3\times3}(\mathbb{R})$, where $M' = -M$:

$$M = \begin{pmatrix} 0 & M_{12} & M_{13} \\ M_{21} & 0 & M_{23} \\ M_{31} & M_{32} & 0 \end{pmatrix} = \begin{pmatrix} 0 & M_{12} & M_{13} \\ -M_{12} & 0 & M_{23} \\ -M_{13} & -M_{23} & 0 \end{pmatrix}$$

And an **outer-score difference matrix** $O \in \mathcal{M}_{3\times3}(\mathbb{R})$ of a score vector S, where $O_{i,j} = S_i - S_j$:

$$O = \begin{pmatrix} 0 & S_1 - S_2 & S_1 - S_3 \\ S_2 - S_1 & 0 & S_2 - S_3 \\ S_3 - S_1 & S_3 - S_2 & 0 \end{pmatrix}$$

By using the least squares criterion, we can use the properties of the Frobenius Norm to formulate the approximation of M by O as a least squares problem:

$$\|M - O\|_2^2 = \left\| \begin{pmatrix} 0 & M_{12} - (S_1 - S_2) & M_{13} - (S_1 - S_3) \\ M_{21} - (S_2 - S_1) & 0 & M_{23} - (S_2 - S_3) \\ M_{31} - (S_3 - S_1) & M_{32} - (S_3 - S_2) & 0 \end{pmatrix} \right\|_2^2$$

Since the **Frobenius Norm** for a given matrix X is equal to $\|X\|_{m\times m} = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{m} |X_{ij}|^2}$. Thus:

$$\|M - O\|_2^2 = [M_{12} - (S_1 - S_2)]^2 + [M_{13} - (S_1 - S_3)]^2 + [M_{21} - (S_2 - S_1)]^2 + [M_{21} - (S_2 - S_1)]^2 \\ + [M_{23} - (S_2 - S_3)]^2 + [M_{31} - (S_3 - S_1)]^2 + [M_{32} - (S_3 - S_2)]^2$$

Which can be formulated as a **least-squares problem with an overdetermined system of linear equations**:

$$Y = X \cdot S$$

$$\begin{pmatrix} M_{12} \\ M_{13} \\ M_{21} \\ M_{23} \\ M_{31} \\ M_{32} \end{pmatrix} = \begin{pmatrix} S_1 - S_2 \\ S_1 - S_3 \\ S_2 - S_1 \\ S_2 - S_3 \\ S_3 - S_1 \\ S_3 - S_2 \end{pmatrix} = \begin{pmatrix} \mathbf{1} & -1 & 0 \\ \mathbf{1} & 0 & -1 \\ -1 & \mathbf{1} & 0 \\ 0 & \mathbf{1} & -1 \\ -1 & 0 & \mathbf{1} \\ 0 & -1 & \mathbf{1} \end{pmatrix} \cdot \begin{pmatrix} S_1 \\ S_2 \\ S_3 \end{pmatrix}$$

One way to find a solution for this overdetermined system is through least squares regression. The solution S^* is the solution such that the difference $Y - X \cdot S$ is very small. We provide different options for computing S^*: *singular value decomposition* (SVD), *QR decomposition* (QR), *normal equations* (NE) and *conjugate gradient* (CG). We choose to solve via **singular value decomposition**, as it is the most accurate least squares method provided by the Eigen numerical linear algebra package for C++.