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Data Mining Through Self Organising Maps Applied on Select Exchange Rates

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I. Introduction

Globalistaion removed most of the barriers to international trade and facilitates large amount of capital flows among countries. The global economies are currently dependent on each other directly or indirectly, thus no economy is independent. When one economy is affected by the financial crises or big scams or any natural disaster, several other dependent economies are affected by these events as they are more integrated presently than ever. The 2008 global financial meltdown caused countries to take various preventive actions to protect their economies from the repercussion. Even Malaysian government released from its reserves about Ringgit 70 billion to stabilise the economy. The effectiveness of relative economic management of two countries converges and reflected in exchange rates (Baillie and McMahon, 1989). The exchange rate (XR) is the linking bond (Bartov and Bodnar, 1994) between any two countries' economies. If home country's economy is not well managed, the XR against every other country's currency will go up which indicates local currency's weakness and the strengthening of the foreign currency against the local currency. International trade and capital flows (Das, 1999) depend on the stability of local currency value and XRs (Ravindran and Hanif, 2010). All international economic activities like tourism, education, financial services in the form of banking, insurance, both foreign direct investments and portfolio investments have strong dependence on XRs (Amihud and Levich, 1985).

Traditional analysis of financial time series (Adya and Collopy, 1998) in parametric statistics have strong assumptions (B. Ripley, 1993) like normality of data, non stationary character of data and non correlated nature of residuals etc (Ravindran et.al 2011). Often they produce limited information for decision making and this information is spurious occasionally. The researchers constantly apply different techniques to understand the root causes for their dynamism and to know their direction of movement in advance (Atiya and Yaser, 1996). Once data is understood in proper perspective, studying and recording their pattern, properties and behavior are easy (E.M. Azoff, 1994). With this objective in mind this paper tries to organise the XRs in Self-Organising Maps (SOM). The SOM concept was proposed by Hopfield in understanding the topological arrangement (J.J. Hopfield, 1982, 1984, 1985) of physical objects by repeated learning with an organised neural network (NN) by adjusting initial values which are assigned arbitrarily by the researcher (Vanstone and Tan, 2005).

II. Literature Review

Neural sciences have been evolving for the last 30 years or so. These biological neurons are equated to artificial neurons and applied in many physical and social sciences. In the last decade, many econometric applications of NN have been tried by the researchers in understanding the properties, behaviour and the pattern of the economic variables such as Gross Domestic Product (GDP), interest rates, share prices (Vanstone and Tan, 2005) and XRs. This study is another attempt to apply NN in XRs to organize them and produce maps, popularly known as Self-Organizing Maps proposed by Nobel laureate Hopfield and applied by Kohonen (Kohonen, 1995; Xinyu Guo et. al, 2007).

III. Self-Organising Maps

Organising the data into the SOM is very important for three major reasons. Firstly, the scattered data which is strewn everywhere is to be organized into a form not only save space but also to organize them

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orderly, to observe whether any pattern (K.S. Fu, 1982; P. M. Grant, 1989) is formed. Secondly the SOM has the ability to reveal the existence of extreme data and this piece of information is extremely useful in data mining. Data mining is very useful in identifying the rogue or fishy transactions. Thirdly, the data could be stored, retrieved and transmitted economically since it is organized. Finally they can be matched with other SOMs to find similarities and deviations like correlation coefficients in parametric statistics to find co movements of data.

IV. Learning by Neural Networks

The NN is working on the principles of learning repeatedly and storing the learnt information in the neurons (K. Jason, 1988). The stored neuron contents will be retrieved back as and when the information is needed for recognition, matching etc. Secondly in data mining especially in ATM transactions the fraudulent are to be isolated from the millions of genuine transactions. This is possible in organizing the data in SOM.

There are two learning methods which are supervised and unsupervised. In supervised learning, there will be a teacher to correct when the student goes out of the right path. Similarly, when the network organizes the data, there will be a target data or threshold data it needs to compare and find the gap. If gap exists, in the next training round, the gap is to be reduced and this reduction is called supervised learning. After several rounds of training if a map is drawn for the learnt stored weights, one could observe a clear pattern emerging from the output of the network (Bartov, 1992; Devroye et.al, 1996).

On some occasions, the target value or threshold value will not be available for finding the gap. In such circumstances, the network will take the individual weights as targets and try to narrow the gap is known as unsupervised learning. In supervised learning the convergence will be faster than unsupervised learning. In this study, unsupervised learning is applied on XRs' returns to organize them in SOM. The command structure of the NN algorithm is given below.

V. Methodology

a) Algorithm

```
Given
    Exchange Rates of 2011 of seven currencies
 Rates are detrended and returns computed

Initialize
 Weights to some small random numbers (50 weekly groups)
 Epoch
 Learning rate, alpha
Iterate
    Repeat
      {
       Pick a return Ri
       Find the Euclidean distance for all weights
            D^2 = (Xi – Wi,j)^2
       Find the shortest Euclidean distance, winning neuron (i,j)
            Wij = min(D^2)
       Update weight of winning, forward and backward neurons
            Wij = Wij + alp(Xi-Wij)   i,j = 1...n
              Wi,j-1 = Wi,j-1 + alp(Xi-Wi,j-1)
              Wi,j+1 = Wi,j+1 + alp(Xi-Wi,j+1)
       Reduce the learning rate
      }
Until the learning rate is negligible
```

b) Data

We have chosen seven countries' exchange rates to perform the SOM mapping. The selected XRs are USD, EUR, GBP, AUD, NZD, JPY and KRW representing two currencies for each continent except Africa. American continent is represented by US dollar only as it is the most popular and globally accepted medium of pricing and transactions. USD is widely accepted by all nations as the benchmark currency and as such, it was treated as a distinct figure. The GBP and EUR represent European continent, JPY and KRW represent the Asia and the Pacific area is represented by AUD and NZD. These nations are also the major trading partners of Malaysia. The required daily XRs were downloaded from pacific XR services website and the analysis was performed. A MATLAB program was written to draw the SOM. The results are presented below.

VI. Results and Discussion

The SOM figures are prepared in three parts, the first part is for the raw returns, the second part is for initial unorganized weights connected by their path in a haphazard manner and the third and final part is for the organized SOM. Hopfield network is used in this experiment and the Kohonen competitive learning algorithm is applied in weight updating and organising the returns. A boundary rectangle is drawn to assess the scatter of returns before organising. The figure will reveal the spread of returns inside the boundary rectangle whether in a concentrated form or spread in various directions. The second part of the graph is assessing the spread of random weights assigned initially and they are connected by lines to see a SOM. The third portion of the graph is the organized SOM which will show the outliers and spread of organized returns.

VII. USD - Ringgit Exchange Rate Returns

USD/Ringgit XR for 2011 is converted into returns to avoid non-stationary character and it is given in the first panel of the above graph in the form of a scatter diagram. The return scatters equally in all four directions of the boundary rectangle which indicates chaotic nature of the spread or behavior. The second panel is showing the 50 weekly representative groups of weights before organizing. The initial random weights spread at all directions of boundary rectangle. Six weights fall on the right hand side while on the left three weights fall. On the top and bottom, only a few weights appear before it is organized. These 50 weekly group weights of the network are trained in an unsupervisory competitive mode for organizing or clustering these returns. When the network is trained, the returns are coming closer and closer in each epoch and form a pattern which falls within the boundary rectangle. Only one weekly group return falls outside the rectangle on the right hand side. Closer observation reveal all weekly return groups are similar and cluster together tightly. The abnormal return falling outside the boundary rectangle may be due to the arrival of new significant positive information to the foreign exchange market because the return falls on the right hand side of the boundary rectangle. In data mining terms this is an abnormal transaction where something fishy.

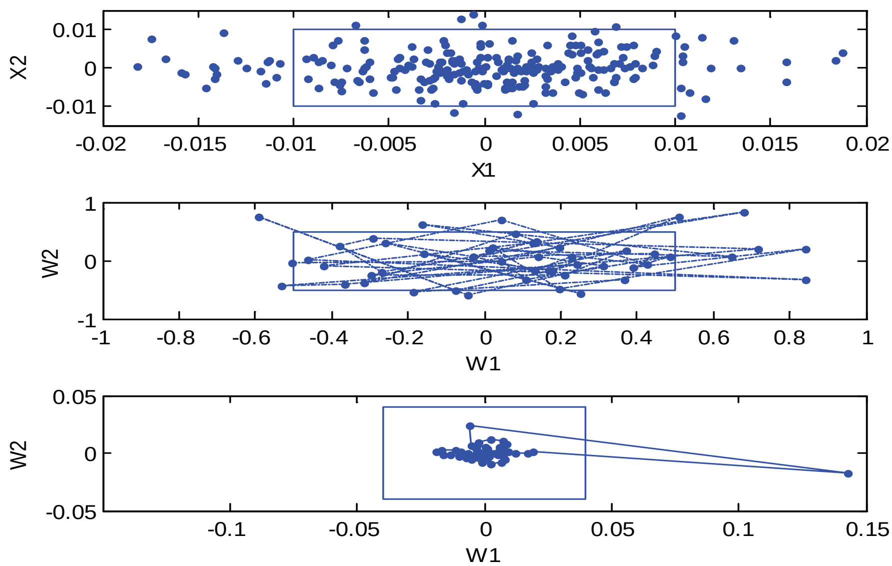
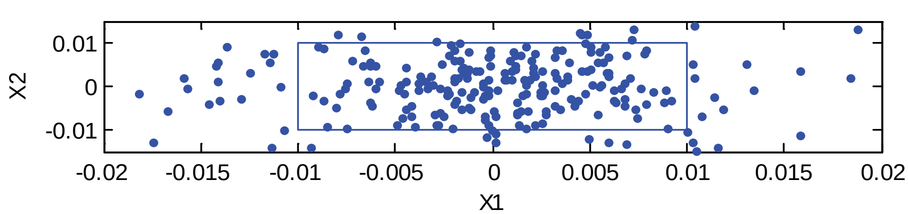


Figure 1 : USD / MYR Returns Self - Organising Map

VIII. Euro - Ringgit Exchange Rate Returns

The Euro XR returns against Ringgit are plotted in the panel one of the graph shown below. The first panel of this figure, the scatter graph indicates a uniform spread in the left, right, top and bottom side of the boundary rectangle. This implies that the rates are normally behaving in 2011. It further indicates the independent and identically distributed nature of the returns. The second panel exhibits the unorganized initial random weights which are generated to cluster 50 weekly groups. These weights are to be trained to cluster the returns on a weekly basis. They spread in all four directions of the boundary rectangle. The third panel shows the organized SOM. In Euro-Ringgit XR also one of the returns falls outside boundary rectangle. But this time it is diametrically opposite to the USD-Ringgit returns. This abnormality may be due to the arrival of significant information to foreign exchange market or may be due to any significant event in Euro zone. A lot of adverse information are emanating from Euro zone area of late. This could be the reason for this outlier.



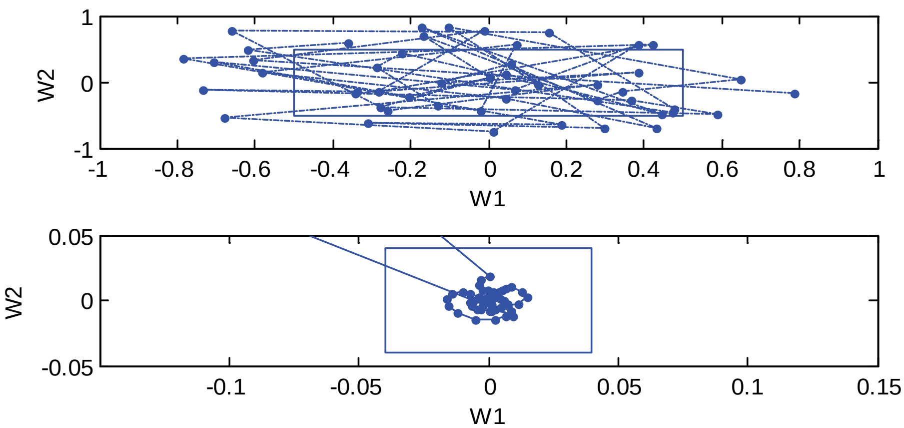


Figure 2 : EUR / MYR Returns Self - Organising Map

IX. Gbp - Ringgit Exchange Rate Returns

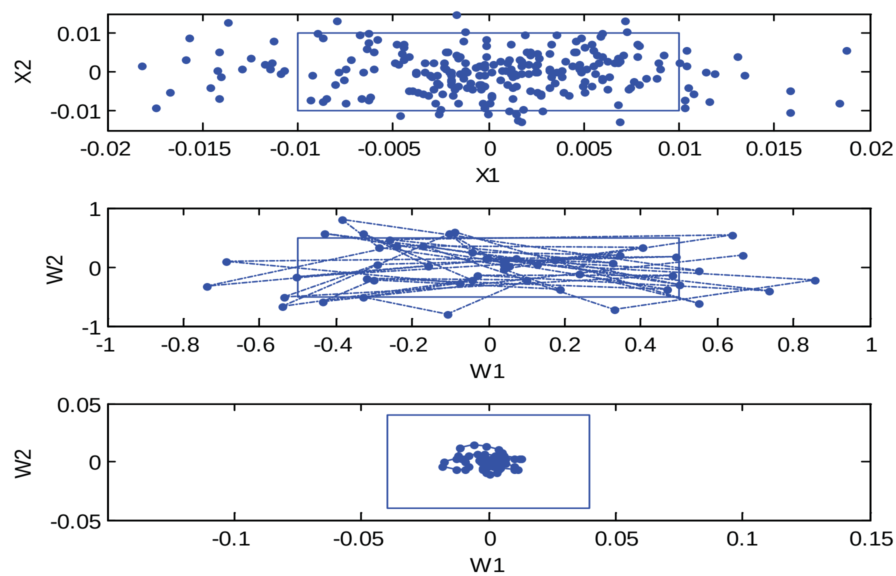
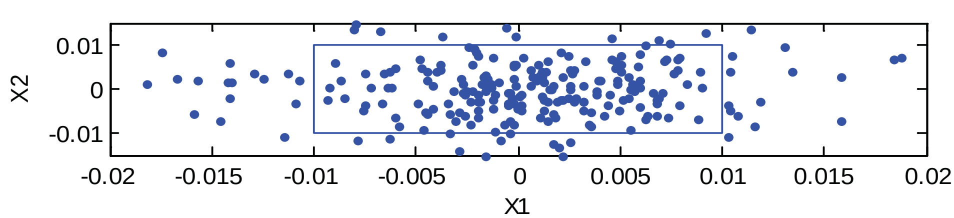


Figure 3 : GBP/ MYR Returns Self - Organising Map

First panel of GBP returns show the spread of returns. They spread in all directions equally which indicates the normal distribution of returns. The middle panel exhibits the initial unorganized weights assigned to train the 50 weeks returns in the competitive learning algorithm. These weights also spread in all directions of boundary rectangle. The last panel shows the organized SOM of GBP. The returns cluster in a compact group and they are placed at the center of the boundary rectangle. It seems there are no abnormal events or information to influence the GBP XRs against Ringgit.

X. Jpy - Ringgit Exchange Rate Returns



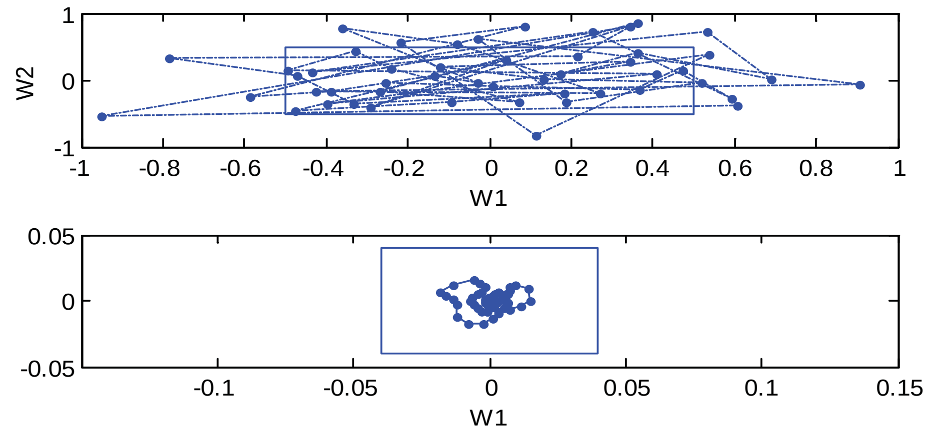


Figure 4 : JPY / MYR Returns Self - Organising Map

The JPY show a uniform pattern in panel one which produces scatter graph for returns in 2011. Panel one of the above graph shows that the initial returns fall inside and outside of the boundary rectangle equally and in all four directions. Panel two gives the scatter diagram of the unorganized random returns which are simulated pure random numbers. In panel three the SOM clustering is similar to GBP and it reveals that the JPY exchange rates against Ringgit are stable without any abnormal behavior.

XI. Krw - Ringgit Exchange Rate Returns

The Korean XR's returns are shown in the first panel of the following graph. The scatter spreads in all four directions equally. The second panel gives the unorganized returns' position which is also fairly spread like the real returns in panel one. The trained and organized SOM of KRW is also tightly clustered like the previous currencies' rates, but one trained rate just falls below the boundary rectangle, like USD rate. But this return is just below the boundary rectangle not like USD which falls at a fairly longer distance. This indicates some moderate information has come to the XR market which has temporarily influenced one of the returns.

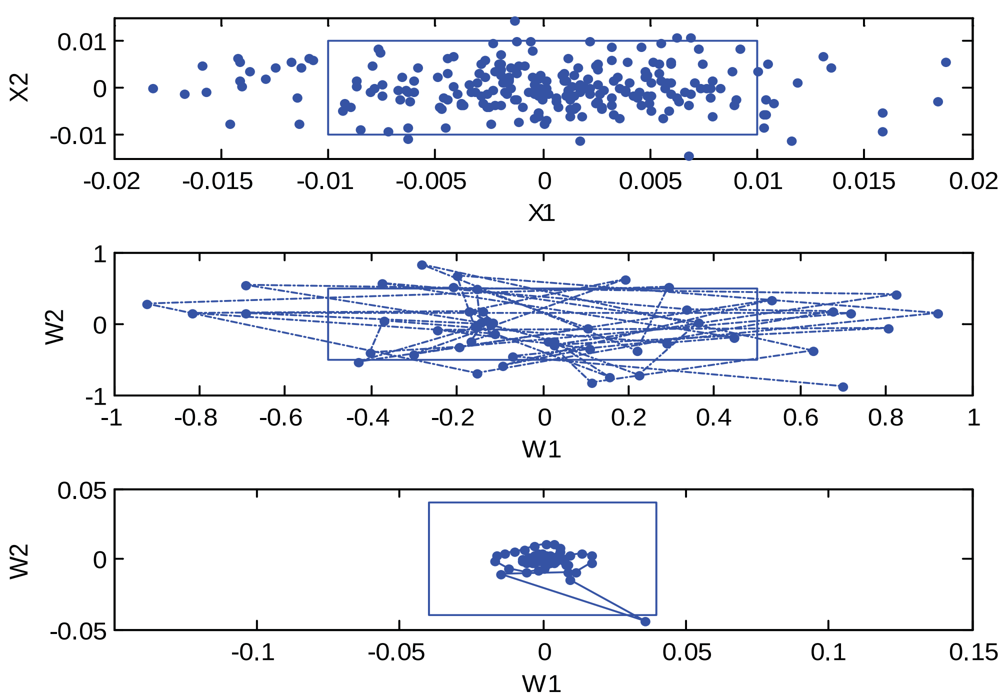


Figure 5 : KRW / MYR Returns Self - Organising Map

XII. AUD - Ringgit Exchange Rate Returns

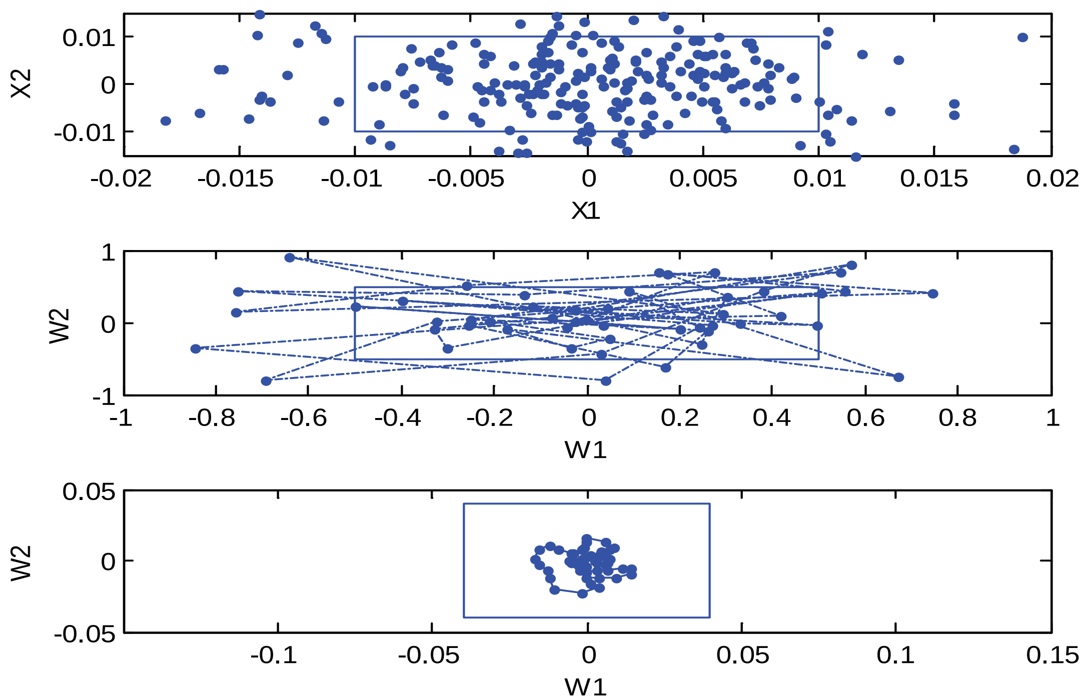
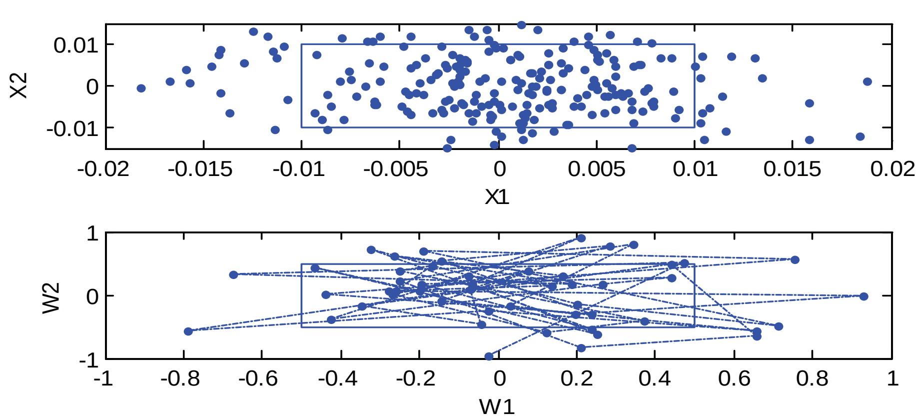


Figure 6 : AUD / MYR Returns Self - Organising Map

The first panel of figure six shows the spread of real returns of AUD. As other XR returns the AUD's returns also spread in all four directions. The second panel gives the random initial weights which will accommodate all 250 returns after training by Kohonen competitive training algorithm. Panel three gives the organized returns after training which are also tightly clustered like other currencies' returns and they are placed at the center of the boundary rectangle as a compact group. It seems AUD returns are also normal and there is no abnormal behavior.

XIII. NZD - Ringgit Exchange Rate Returns

The AUD and NZD XR returns behave more or less similarly. The NZD scatter diagram shows spread in all four directions of the boundary rectangle. The unorganized weights given in panel two spread more on the right hand side of boundary rectangle. When the returns are organized into 50 weekly groups after training, they show a pattern closely knit compact group placed at the centre of the boundary rectangle. This implies that both AUD and NZD XRs returns organize similarly in SOM.



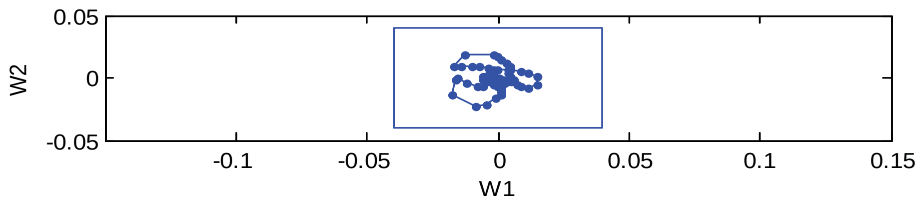


Figure 7 : NZD / MYR Returns Self - Organising Map

The above SOMs help in pattern recognition, organizing the data for storing and data mining purposes. XR returns of 2011 show a very tight compact clustering and placed well at the center of the boundary rectangle with three exceptions. This shows the economic stability and better management of these countries' economies by the respective governments and the central banks.

VI. Conclusion

SOMs are important in data storing, data mining, pattern recognition etc. We applied exchange rates to prepare SOMs for seven popular currencies' exchange rate returns. The SOMs are prepared in three parts, the first part was for the raw returns, and the second part was for 50 unorganized initial random weights which are haphazardly connected to each other. The third and final panel represents the organized SOM. Hopfield network was used in the experiment and the Kohonen competitive algorithm was applied in organizing the returns. The first part of the SOM the returns spread inside, outside, top and bottom of the boundary rectangle equally for all currencies. The second panel which is prepared with initial unorganized weights scattered in all directions of boundary rectangle as it appears in panel one. The third portion of the graph is the organized SOM which is prepared after training the weights with returns in Kohonen competitive algorithm. These returns are well organized and placed within the boundary rectangle except USD, Euro and KRW. One outlier is present in these currencies returns and they fall outside the boundary rectangle. These are outliers and may have arisen due to the arrival of some significant information to the exchange rate market. They are to be investigated to know in which week these are behaving like this and for what reason. This research lays the foundation for the behavior of the exchange rates in the form of SOM.

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MATLAB Program

```
close all
clear all
clc

load currency1
y=1./data;                    % Find direct exchange rate
x11=y(504:753,:);                   % 2011 data

%% Descriptive of exchange rates

ret11=price2ret(x11);               % Rates are converted to returns
x=[ret11(:,1)' rand(250,1)-0.5]';   % Exchange rate returns scattered
w=[rand(1,50)-rand(1,50); rand(1,50)-rand(1,50)]; % Random weights

%% Figure for returns scatter

figure
plot([-0.5 0.5 0.5 -0.5 -0.5],[-0.5 -0.5 0.5 0.5 -0.5]) % Rectangle
xlabel('X1')
ylabel('X2')

hold on
plot(x(1,:),x(2,:),'b.')            % Exchange rate returns scatter
axis([-1 1 -1 1])

%% Figure for unorganized returns
figure
plot([-0.5 0.5 0.5 -0.5 -0.5],[-0.5 -0.5 0.5 0.5 -0.5]) % Rectangle
xlabel('W1')
ylabel('W2')
hold on
plot(w(1,:),w(2,:),'b.',w(1,:),w(2,:),'-.') % Unorganised weights
axis([-1 1 -1 1])

%% Program parameters
alp=0.9;                                  % Learning rate
ite=1;                                    % Start the learning loop
epoch = 0;                                % Epoch counter

while ite
for i=1:250                               % 250 exchange rates per year
    for j=1:50                      % Weekly grouping
        d=sum((w(:,j)-x(:,i)).^2);  % Find Euclidean distance
```

```
        d1(j,:)=d;                  % store d in d1 for finding winner
    end
 [wn wi]=min(d1);       % Minimum distance is the winner neuron
 fwd=wi+1;              % Forward neuron
 bwd=wi-1;              % Backward neuron
 if bwd<1, bwd=50; end  % If end is 0 then column is 50
 if fwd>50. fwd=1; end  % If end is 50 then column is 1
 w(:,wi)=w(:,wi)+alp*(x(:,i)-w(:,wi));     % Update winner neuron
 w(:,fwd)=w(:,fwd)+alp*(x(:,i)-w(:,fwd));  % Update forward neuron
 w(:,bwd)=w(:,bwd)+alp*(x(:,i)-w(:,bwd));  % Update backward neuron
end
  alp=alp*.9;           % Reduce the alpha rate or annealing
if alp < 0.01              % If alpha is too small
        ite=0;                % Stop the iteration
end
  epoch=epoch+1;        % Epoch counter
end

%% Figure for the self organized map
figure
plot([-0.5 0.5 0.5 -0.5 -0.5],[-0.5 -0.5 0.5 0.5 -0.5])
xlabel('W1')
ylabel('W2')

w = [w w(:,1)]             % Connect the last and first returns
hold on
plot(w(1,:),w(2,:),'b.',w(1,:),w(2,:))
                                 axis([-1 1 -1 1])
```