Exchange Rates Inquiry and Analysis

Course Project for Big Data Analysis

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Abstract—With the international trade and commerce being of more importance, it's necessary not only for a specific group of industries but also for all of us to gain daily access to the updated currency rates. With more convenience in getting the exchange rate information, people are equipped with more related knowledge to make better decisions regarding to the currency market. This paper briefly introduces our group of work in obtaining, analyzing and displaying exchange rates. From the related analysis including regression and clustering, up to the building and configuration of a website, our course project has achieved a rather complete and satisfactory result in respect of our primary goal of design.

Keywords-webpage building; website setup; rate prediction; trading advise

I. INTRODUCTION

Today is Information Age. If you can't get the newest info, the loss caused may reach million dollars. This is particularly important in financial industry.

That is how Bloomberg success, by providing the latest information, professional analysis and reasonable prediction.

From all finance elements, we think that rate exchanges is a very important one, which has a great influence on stock market.

So we designed a website works like Bloomberg. In this website you can see live rate exchange table, get currency convert and read the analysis and prediction of currency exchange rates.

II. RELATED WORKS

Many website including famous Bloomberg are doing this job. And so many economists are trying to get something form international currency exchange rates.

As long as a paper or website related to finance, there is something about exchange rates.

So let's see what we can do about it.

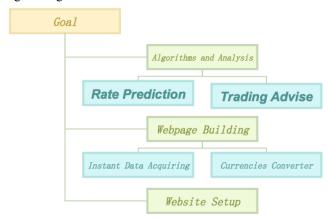
III. SYSTEM OVERVIEW

Our project is divided into two parts works, one is website design and setup, the other is algorithms to do analysis on dataset.

The dataset we used are: Forex, WTI&Europe Brent Spot Price, GDPs and Bloomberg live exchange rates.

The target exchange rates used in analysis algorithm is USD/HKD.

The prediction and classification algorithm we used is logistic regression.



IV. ALGORITHMS

Our target is to successfully predict the USD/HKD on the next trading period, data collected frequency is daily for training data and monthly for testing data respectively. Datasets:

- 1. Forex—Cross Exchange Rates
- 2. WTI&Europe Brent Spot Price
- 3. GDPs
- 4. Global Financial Data

There are two ways to predict one country's exchange rate. One is to construct a determining function of the exchange rate using factors such as GDP, PPP, price of gold, price of oil, etc. The kernel point is to come up with the corresponding coefficient of every factor and then do prediction by calculating the exchange rate using this function. The other way is to use the exchange rates of other countries that have similar exchange rate run charts with the targeting country over the past years and do predictions.

For the first train of thought, we use logical regression function (on Mahout) to predict whether the exchange rate will increase or decrease, regression function and stepwise regress function to determine the coefficients of the corresponding factors and analyze which factors play the main part in determining the exchange currency while which factor adversely affect the accuracy of using linear regression to predict the exchange rate. For the second way of thinking, we also write codes using mahout running on eclipse to do clustering for exchange rates of 40 different countries, so that to determine which countries have close connections and use countries in the same cluster to predict a particular country's exchange rate in this cluster.

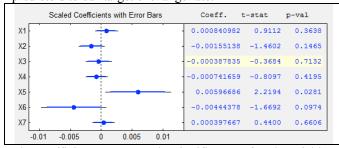
A. Data Pre-Processing:

We pre-process the gathering data with the following four stages:

- 1. Centering and scaling
- 2. Standardized sampling frequency to monthly;
 - a) Interpolation. It is noticed that GDPs are updated quarterly, so bi-linear interpolation method was used when up-sampling the GDPs to monthly.
 - b) Down sampling. More specifically, for data in Forex, the Open, Close, Bid and Ask prices has been extracted and down-sampled into daily
- 3. Calculate variables that are functions of time series:
 (1) Average Mean from the history, (2) Difference,
 (3) Inner Production, (4) Aroon
- 4. Remove irrelevant predictors and remove the outliers of the target cases in datasets, there are two main potential advantages to remove predictors prior a model is trained, (1) is less predictors means less computational complexity, and (2) is for some modeling method such as regression models, they are sensitive to predictors which have degenerate distribution or have low correlation to the target cases. By removing the outliers from the training dataset, a refined model with better performance is obtained. More details of this part will be demonstrated in the following section.

B. Use fundamentals as well as technical factors to predict movement of the exchange rate:

Firstly, use stepwise regression to explore important predictors to our target exchange rate:



The coefficient represents the significance of each variables, from the table on right side we can see the most significant Variables are X1(Trading_Volume), X2(Gold Price), X5&X6(Oil Price). They have the largest coefficients, at the

same time, however they also provide the largest validity to the prediction based on their evaluation on P values.

For regression method, it is important to

Based on the analysis above, we then chose following four predictors to form an expression of USD/HKD:

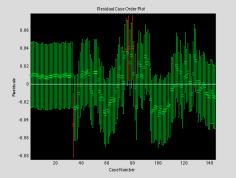
Trading Volume(X1)

Gold exchange rate(X2)

Europe Brent Spot Price(X5)

Average Mean of close prices for last 5 days from sampling date (X6)

With the four predictors showing above, assuming that target cases with too large error range are actually outliers, plot the residuals along with each case's error range, outliers are shown with red bars, removed from both training and testing sets

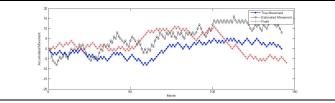


Based on the most significant variables, a movement predictor is then conducted, by discretize the target exchange rate into finite categories upward and downward, classification algorithms can then be used into prediction of the movements. Swipe for all possible parameter space(training rate, passes number) to obtain an optimal performance, which means the largest AUC, which means the possibility of predicted positive scores larger than the predicted negative scores.

AUC	Confusion Matrix		
0.60	49	30	
	32	32	

This classifier is treated as our base-line approach

C. Trading strategy advisor:



If movements obtained, assume every long or short action will either gain 1 unit or lose 1 unit with no bias. Profitability will be 13.10%

This estimation method is trivial that profitability will be unconvincing to the professionals with finance knowledge, in the stock market people tend to "hold" and wait if the earning smaller than a threshold because they are expecting a better performance of this currency in the future.

D. Technical factors of exchange rate from other currency as predictors

In this section, same logistic regression model is used, but with optimization process and different set of predictors. Here's the currencies under the USD which we chose:

US	US	US	US	US	US	US	US
DB	DC	DD	DH	DJP	DP	DS	DT
RL	AD	KK	UF	Y	LN	EK	RY

More specifically, we construct several predictors with the first-order differences as well as their AROON indicators. Still, we first construct a logistic-regression classifier

mahout org.apache.mahout.classifier.sgd.TrainLogistic --passes 100 --rate 0.1 --lambda 0.001 --input /home/bigdata/openpricetoUSD.csv --output /home/bigdata/exchange_rate.model --target USDHKD --categories 4 --predictors USDBRL USDCAD USDDKK USDHUF USDJPY USDPLN USDSEK USDTRY --types n n n n n --features 5

AUC	Confusion Matrix		
0.64	27	20	
	38	57	

AUC score is higher as the more overall correct classified cases have incurred, correct classification number is 27 for upward cases and 57 for downward cases, the outcome is inbalanced. Based on the stepwise regression approach, removed non relevant predictors: USDJPY, USDSEK, USDTRY

AUC	Confusion Matrix		
0.64	24	20	
	38	62	

Only slightly improvement has been observed, outcomes are still un-balance

One explanation is because of the growing GDPs in China, the productivities of the labor force has been increase these years, so that observations of upward movement of HKD/USD are more frequent, thus downward movements of USD/HKD are more frequent. In the following experiments, maintain the possibilities of upwards and downwards to 0.5, adjust HKDUSD to two categories, in addition to that, the 2 bits Uniform-Quantization transformation all predictors into four steps.

AUC	Confusion Matrix		
0.67	45	28	
	26	43	

Expression of USDHKD with the five predictors are shown below:

USDHKD ~ 0.035*Intercept Term + 0.207*USDBRL + 0.044*USDCAD + 0.207*USDDKK + 0.035*USDHUF + 0.207*USDPLN

E. Classifier constructed by Random-Forest

When working with a continuous predictor and a categorical response, the process for finding the optimal split point the samples are sorted based on their predictor values. The split points are then the midpoints between each unique predictor value. In our case, the response will be 2 bits, 00 for downwards, 01 and 10 for holding interval and 11 for upwards, a 3×3 contingency table at each split point is generated:

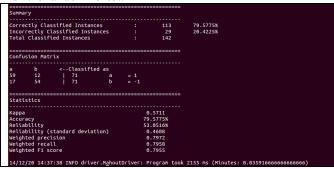
<i>_</i> 1 u	icu.				
		UPWA	HOL	DOWNW	
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			0		
	<split1(00)< td=""><td>N11</td><td>N12</td><td>N13</td><td>N</td></split1(00)<>	N11	N12	N13	N
					+
					1
	>SPLIT1(01),	N21	N22	N23	N
	<split2(10)< td=""><td></td><td></td><td></td><td>+</td></split2(10)<>				+
	, ,				2
	>SPLIT2(11)	N31	N32	N33	N
	, ,				+
					3
		N1+	N2+	N3+	N

As shown in the table, at least 2 split points have to be set for every continuous predictors. Similar to what has demonstrated in the previous regression classifying sections, Uniform-Quantization is implemented here to generate the two split points.

According to all the discussion above, a classifier can be constructed, details of the classifier is shown below:

Forest Nodes	28540		
Forest Avg, Nodes	285		
Forest mean max	17		
Depth			

Here's a screen-shot showing the performance of classifiers for the random forest:



F. Clustering with the dataset of annually exchange rate of 40 countries from 1960 to 2013

We collected and processed the exchange rate of 40 countries(Nigeria, Malawi, China, Germany, Venezuela, Kenya, Korea, Kuwait, Myanmar, Pakistan, Sweden, USA, Jordan, Columbia, Japan, Cape Verde, Comoros, Oman, Paraguay, Costa Rica, Egypt, Morocco, Canada, Finland, France, Greece, Iceland, Italy, Libya, Malaysia, Mauritius, Mexico, Nepal, Norway, Panama, Poland, Romania, Spain, Sudan, UK) spanning from 1960 to 2013. The dataset is attached to this project report. (all data collected from GlobalFinancialData.com)

We do clustering using mahout running on Eclipse. The step is as follows:

- 1. Generate vectors from input dataset
- 2. Write vectors to input directory
- 3. Write initial cluster centers
- 4. Run clustering algorithm with vectors and initial cluster centers. We choose KMeans clustering with Euclidean Distance Measurement.
- 5. Read clusters from output directory

We do clustering with this dataset using different ks(k=3, k=5, k=8, k=10), i.e. clustering 40 countries according to their exchange rate to 3, 5, 8, 10 clusters.

After processing the output, the results come as follows,

3 clusters

cluster 0:

Korea, Comoros

cluster 1:

Columbia, Paraguay

cluster 2:

Nigeria, Malawi, China, Germany, Venezuela, Kenya, Kuwait, Myanmar, Pakistan, Sweden, USA, Jordan, Japan, Cape Verde, Oman, Costa Rica, Egypt, Morocco, Canada, Finland, France Greece, Iceland, Italy, Libya, Malaysia, Mauritius, Mexico, Nepal, Norway, Panama, Poland, Romania, Spain, Sudan, U.K.

5 clusters

cluster 0:

Korea, Columbia

cluster 1:

Paraguay

cluster 2:

Japan, Comoros, Costa Rica

cluster 3:

China, Germany, Venezuela, Kuwait, Sweden, USA, Jordan, Oman, Egypt, Morocco, Canada, Finland, France, Greece, Italy, Libya, Malaysia, Mauritius, Mexico, Norway, Panama, Poland, Romania, Spain, Sudan, U.K.

cluster 4:

Nigeria, Malawi, Kenya, Myanmar, Pakistan, Cape Verde, Iceland. Nepal

6 clusters

cluster 0:

Korea, Columbia

cluster 1:

Paraguay

cluster 2:

Nigeria, Malawi, Kenya, Myanmar, Pakistan, Cape Verde, Iceland, Nepal

cluster 3:

Germany, Venezuela, Kuwait, USA, Jordan, Oman, Egypt, Canada, Finland, France, Greece, Italy, Libya, Malaysia,, Panama, Poland, Romania, Spain, Sudan, U.K.

cluster 4:

China, Sweden, Morocco, Mauritius, Mexico, Norway

cluster 5:

Japan, Comoros, Costa Rica

8 clusters

cluster 0:

Korea, Columbia

cluster 1:

Myanmar, Costa Rica

cluster 2:

Nigeria, Malawi, Kenya, Pakistan, Cape Verde, Iceland, Nepal

cluster 3:

Sweden, Morocco, Mauritius, Norway

cluster 4:

China, Egypt, Malaysia, Mexico

cluster 5:

Japan, Comoros,

cluster 6:

Paraguay

cluster 7:

Germany, Venezuela, Kuwait, USA, Jordan, Oman, Canada, Finland, France, Greece, Italy, Libya, Panama, Poland, Romania, Spain, Sudan, U.K.

10 clusters

cluster 0:

Korea, Columbia

cluster 1:

Comoros, Costa Rica

cluster 2:

Mauritius

cluster 3:

China, Sweden, Morocco, Mexico, Norway

cluster 4:

Venezuela, Egypt, Malaysia, Poland, Romania, Sudan

cluster 5:

Japan

cluster 6:

Paraguay

cluster 7:

Germany, Kuwait, USA, Jordan, Oman, Canada, Finland, France, Greece, Italy, Libya, Panama, Spain, U.K.

cluster 8:

Myanmar

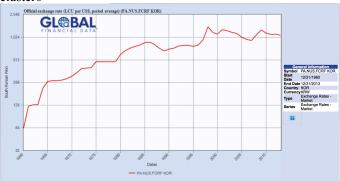
cluster 9

Nigeria, Malawi, Kenya, Pakistan, Cape Verde, Iceland, Nepal

We can see from the result that as k gets lager, every cluster gets smaller and nodes in the same cluster have a more significant correlation with each other.

For example, with the 3-cluster clustering, Korea and Comoros are clustered to

cluster0



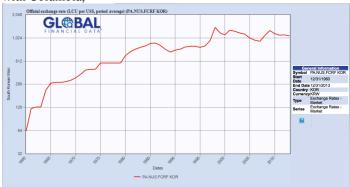
Exchange rate -- Korea Won per US Dollar from 1960 to 2013



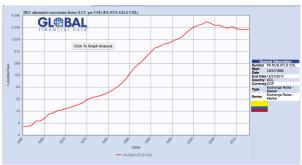
Exchange rate -- Comoros Franc per US Dollar from 1960 to 2013

We can see from the graph that the Exchange rate against US Dollar of Korea and Comoros has the similar fluctuation range (mainly 100 - 1000), however, their trends(shapes) aren't very similar. Korean Won kept growing over 1960 – 2013 in general, while Comoros Franc kept the same from 1960 to 1970 then had 2 rounds of distinct fluctuations.

As to the 10-cluster clustering, Korea is clustered together with Columbia,



Exchange rate -- Korea Won per US Dollar from 1960 to 2013



Exchange rate -- Columbia Peso per US Dollar from 1960 to 2013

From these 2 graphs, we can see that Korean Won and Columbia Peso go with similar growing trend and grow with similar scope – a closer relationship between them compared with the relationship between Korean Won and Columbia Peso.

To take another example, we will examine countries in the same cluster with USA.

When k = 3, they're {Nigeria, Malawi, China, Germany, Venezuela, Kenya, Kuwait, Myanmar, Pakistan, Sweden, USA, Jordan, Japan, Cape Verde, Oman, Costa Rica, Egypt, Morocco, Canada, Finland, France Greece, Iceland, Italy, Libya, Malaysia, Mauritius, Mexico, Nepal, Norway, Panama, Poland, Romania, Spain, Sudan, U.K.};

When k = 5, they're {China, Germany, Venezuela, Kuwait, Sweden, USA, Jordan, Oman, Egypt, Morocco, Canada, Finland, France, Greece, Italy, Libya, Malaysia, Mauritius, Mexico, Norway, Panama, Poland, Romania, Spain, Sudan, U.K.};

When k = 6, they're {Germany, Venezuela, Kuwait, USA, Jordan, Oman, Egypt, Canada, Finland, France, Greece, Italy, Libya, Malaysia,, Panama, Poland, Romania, Spain, Sudan, U.K.};

When k = 8, they're {Germany, Venezuela, Kuwait, USA, Jordan, Oman, Canada, Finland, France, Greece, Italy, Libya, Panama, Poland, Romania, Spain, Sudan, U.K.};

And when k = 10, they're {Germany, Kuwait, USA, Jordan, Oman, Canada, Finland, France, Greece, Italy, Libya, Panama, Spain, U.K.};

From k=3 up to k=10, the number of countries in the same cluster with USA keeps decreasing and the features these countries share become apparent. For k=3, 37 out of 40 countries are in this cluster – almost all the 40 countries. While when it comes to k=10, countries in this cluster are almost Western European countries and countries using USA dollars, who have real close economical as well as political connections with each other.

V. WEBPAGE BUILDING

Webpage design is a rather strange topic to all of us group members so we had to learn from the sketches. The languages we used include HTML, CSS, JavaScript and JSP.

Aside from making the UI more user-friendly, the emphases is to get live exchange rate data from Bloomberg and to design a currency converter based on that.

Webpage address: http://exchangerate.com.s3-website-us-west-2.amazonaws.com/

A. Obtaining Live Exchange Rates from Bloomberg

- We got JS source form http://www.bloomberg.com/hscommon/calculators/currdata.js
- In the html code, use JavaScript function document. write() to get the live exchange rates we need and write them in Live Exchange Rates table of webpage.
- Design webpage to update automatically every 5 seconds, by doing this could ensure the rates in table is synchronous with Bloomberg.
- Webpage Screenshot



B. Designing a Currency converter

- Use JS source
 http://www.bloomberg.com/jscommon/calculators/finance.js
 http://www.bloomberg.com/jscommon/calculators/m
 ktscurrcalc.js
- Write JavaScript functions to calculate currency exchange result.
- Use CSS and JavaScript to design select function.
- Webpage Screenshot

Currency Converter

amount: 100.00 GBP - British Pound CNY - Chinese Yuan Renminbi CONVERT

C. Graphic and UI Design

 Design the index page and organize the whole website by certain hierarchy.

Insert the picture slider and implant the pictures.

• Insert the main content and set up hyperlinks.

Add some nice footers.

 Design different pages other than the index page and make sure the hyper links between pages actually work.

VI. WEBSITE SETUP

We have thought of several ways to setup our website so that everyone could get access to our result presentation, however, with insufficient fund, few of them actually work. Finally, we have decided to deploy our website using the Amazon Web Services (AWS) by Amazon.

AWS is a collection of remote computing services, that altogether make up a cloud computing platform since 2006. The most central and well-known of these services are Amazon EC2 and Amazon S3. EC2 provides virtual servers in the cloud that has more computing power than physical servers and S3 provides scalable storage in cloud, which allows us to upload our webpage design and host our own static website.

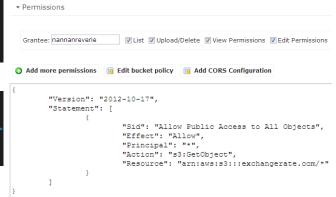
AWS allows developers to use the basic services for free for the first 12 months thus is an ideal platform to setup our own website.

Following are the basic steps to build a rather simple website.

1) Create related buckets for the website.



2) Add permissions to the properties of the website to make sure everyone online can see our job.



3) Enable logging to keep track of the number of visitors.

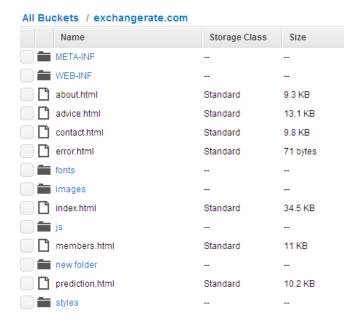
▼ Logging

```
Enabled: 

Target Bucket: logs.exchangerate.com

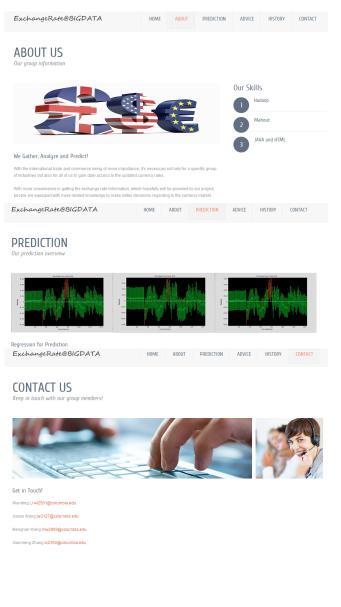
Target Prefix: root/
```

4) Upload all the files for webpage design with the same hierarchy.



5) Host the static website and check the result by typing the domain name directly and make further modifications.





VII. SOFTWARE PACKAGE DESCRIPTION

In the design of webpage part, we use software eclipse, tomeat, language HTML, CSS, JavaScript and JSP.

In the setup of website part, we use Amazon Web Service. In the algorithm of analysis part, we use Hadoop, Mahout, Matlab and java.

The screenshots of our website could be seen in part V and VI.

All source code could be seen in GitHub.

VIII. CONCLUSION

For the analysis part, we firstly pre-processed the datasets with four stages, from the pre-processing stage, data were centered and scaled, sampling rate is unified, and technical factors were calculated, then some irrelevant predictors were removed from the predictors set, at the same time, outliers in the target cases (i.e. USD/HKD historical rates) are detected and removed.

Then some classifying approaches have been implemented, a un-optimized model using logistic regression was first constructed, not only this model is used as base-line approach, this model also helped detect outliers for target cases. In addition a naïve profits estimation approach was designed to show the overall probability.

Based on the optimization process, a refined regression model was constructed. In this model, firstly a filtered datasets has been used, at the same time other currency historical data have been used. Secondly all predictors were quantized into four steps values, and target cases have been balanced to equal possibility. Classifying AUC scores is 0.67, and 12% of the performance increase is observed for all the optimizing process.

A random forest classifier was then constructed, first set two split points for every continuous predictors, in our case they are other currency exchange rates, based on the prediction response, a trading advise strategy is proposed.

Clustering approaches were also implemented, from the results and analyses above, we can use clustering of exchange rate to judge the development status, as well as the development prospect of targeting countries, speculate

whether there exists a close connection among targeting countries, and at the same time, predict a certain targeting country's exchange rate using other countries' data in the same cluster.

ACKNOWLEDGMENT

We authors would like to thank Professor Lin and all TAs in Big Data Analytics. We learned a lot about how to do analysis on big dataset, which is pretty useful for our future work and study.

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