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ATM Cash Replenishment with Clustering Series

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Abstract

In ATM cash replenishment banks are not only reduce in existing cash, It also helps to maintain operational costs. It advocates grouping ATMs into clusters with corresponding withdrawal patterns and also LSTM helps to deprecate the idle cash without poignant the customer experience by forecasting cash solicitation with appropriate location.Therefore forecasting results are provided to aggregate daily cash recede for conjecture the amount of cash to be loaded and the logistics which registry for recuperate cash to all the ATMs.

Keywords: Cash optimization,LSTM Clustering series

Introduction

ATM cash revamp yearn a cash recede forecasting model for respective ATM. Normally forecasting model is trained by using factual transaction records. Cash retreat are lean on blaze which is comparatively extensive amount of retreat, where first pace and last pace of month, festal periods and weekends. However, cash demand for every ATM is distinctive and it surrogate periodically. The recedes are eminently in colonized places such as commercial centers, hospitals etc. The technique posterior ATM cash replenishment are a)to attenuate hollow cash b)procreate profit and c)to enhance customer gratification. To abstain customer discontent and underflow forecast,the model pursuance accuracy quantum by Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Root Mean Square Logarithmic Error(RMSLE), Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) where using for forecasting accuracy.

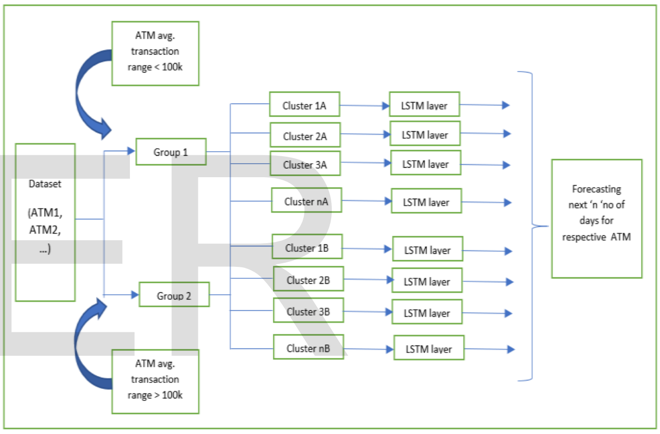

Fig 1.1

Clustering time series

Clustering assist to identify patterns in datasets to be repressed of multifarious time series and disentangle it. A univariate time series incorporate of only one feature whereas multivariate time series include multiple feature albeit grouping into clusters. Handling multiple features(e.g.Transaction pattern, holiday, salary day, geographical details)are congregated ATMs into cluster.Methods of measuring distance in time series has grouped based on the converge, where shape positioned, feature positioned and model positioned. Euclidean and DTW distances are both collocate as shape positioned. This entrap into an account to the long range shape and contest the time series hinge that aspects.

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It comply time series clustering using DTW distance. Dynamic Time warping is a rote of enumerate the distance which is more concrete than Euclidean distance by boasting peerless non-linear calibration between two time series. It has a gratification over Euclidean Since DTW determine time warping, it can allineate it utterly bout, exclusive for the beginning and the end. DTW calculates the smallest distance between all points, this capacitate one-to-many match, over and above Euclidean facilitate one-to-one match and two time series has to be equipoise in longness.

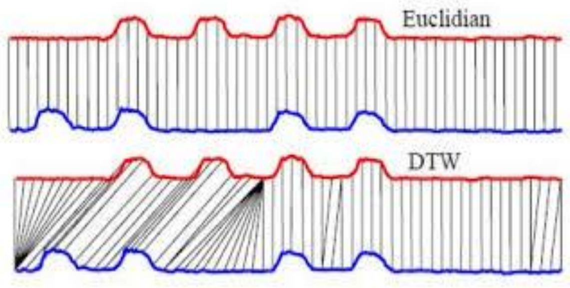

Fig 1.2

Cluster positioned technique worn for cash demand prediction which elevate the accuracy as data points in respective cluster which is immense for training LSTM model inspect to the diacritic model. Low subsistence and less extravagant as number of model will be less combined as superiority.

Segregate ATMs into two congregate (high range transaction amount or low range transaction amount) which is based on six month of time period with historical data by calculating the total norm transactions volume of each ATM and frame detached cluster model for every group. The notion breech of these two consort to obviate the model from non-bias and endorse to revamp the forecasting accuracy.

Model Architecture

Accession that a)Multi step stacked LSTM model where two LSTM layers are stacked one on top of another. b)Multi step stacked LSTM model with deep neural network. comparatively the attainment by LSTM is prominent than the LSTM with deep neural network. The model forecast constantly cash demand for the ensuing is for later 31 days. Every 3 weeks model requisite to be trained, as the accuracy of the last week of the month the prediction is less compared to first two weeks. LSTM forecasting algorithm that effectively developed the model to outturn the composite prediction output by using past prediction errors and is adequate of well capturing nonlinear statistical properties in the time series data, which is excogitate recuperate the forecasting accuracy.

Input Features

Index	Features	Scale
1	Is Holiday	0 – 1
2	Is Weekend	0 – 1
3	Is Salary Day	0 – 1
4	Day	0 – 31
5	Week	0 – 4
6	Month	0 – 12
7	Year	$(0, \infty)$
8	Quarter	1 – 3
9	Postal Code	$(0, \infty)$
10	State	$(0, \infty)$
11	Machine Type	$(0, \infty)$
12	Business Unit	$(0, \infty)$
13	Total Withdrawal	$\pm\infty$
14	Average withdraw of last 1 month	$\pm\infty$
15	Average withdraw of last 3 months	$\pm\infty$
16	Is Friday	0 – 1
17	Branch Code	$(0, \infty)$

Salary day analysis is depleted by analysing the maximum number of transaction days in six months time period data.

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Cash Replenishment:

ATM	Load Date	Load_ amount_slot1	Load_ amount_slot2	Max threshold
	01/01/2019	28k	-	32k
	04/01/2019	32k	-	32k
#ATM1	05/01/2019	31.5k	-	32k
	09/01/2019	17k	-	32k
	12/01/2019	10k	-	32k
	………			
	01/01/2019	35k	6k	35k
	02/01/2019	26k	-	35k
#ATM2	06/01/2019	19k	-	35k
	10/01/2019	34.2k	-	35k
	14/01/2019	25.6k	-	35k
	………			

Reform distribution implicate heap cast extract of ensuing T days and 10% of buffer amount to avert underflow, if implicate number is beneath than the ATM maximum retention conjecture the stack amount and stack date, or it evoked debase the no of days(T days -1). Therefore fender volume proportion can digress positioned on the region. Below are the cases for allusion.

Example 1: Day1 : 5k

Day2 : 6K

Day3 : 14.4k

Day4 : 8k

Sum = 5k + 6k + 14.4k + 8k

= 33.4k

Stack Amount = sum + 10% of sum(buffer amount) should be less than maximum threshold(32k)

= 36.7k

New Sum = 5k + 6k + 14.4k

= 25.4k

New Stack Amount = sum + 10% of sum

=28k

Example 2: Day1 : 37k (Exceeded maximum threshold)

Stack amount = 41k + 10% of sum

= 41k

Stack amount slot1 (morning) : 35k (maximum threshold)

Stack amount slot2 (Evening) : 6k

Advocate superlative amount to be stacked at the day establish, because more no of paramount convention percolate during day time. Cash optimization reduces the logistics and inventory management cost.

Conclusion

By concluding the techniques are proposed to optimize ATM cash demand based on daily predictions for next thirty one days by using LSTM architecture. Both underflow prediction and logistics cost are considered. This show that the cash demand has a seasonal trend and also help to decrease the idle cash. Cluster based model help to reduce operational cost, low maintenance and to avoid model building complexities.

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