# **Time Series Forecast with Neural Networks**

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## **Abstract**

This project aims to implement and compare various methods for Time Series Forecasting, since the classical ones, such as ARIMA and GARCH until Recurrence Neural Networks and Prophet. The goal is to evaluate if the later, and more complex methods, necessarily result in better forecasting, with respect to the RMSE metric or if simpler methods are precise enough to be chosen for either stationary and non-stationary financial series.

## 1. Introduction

Implementing precise models for Time Series Forecasting is crucial to various areas of knowledge, being fundamental to Financial Analysis of Stock Returns and Currency, which are types of time series chosen to be worked with. For that purpose, one could say that is a difficult task to chose between the huge amount of different methods, since each of them have its own advantages and disadvantages. For instance, simple linear models such as ARIMA are easy to understand and implement, but may be too simple and inflexible to model Stock Returns. On the other hand, MLPs and Recurrence Networks may present themselves with precise forecasts but with a complex theory behind and possible training difficulties may arise - over fitting is a classic example.

With being said, this project's goal is to implement different time series methods for 3 financial time series, all them with a stationary and non-stationary form, so that one can compare the quality of each model prediction.

# 2. Methodology & Experimental Results

Three financial time series were chosen to be used in this project. All of them have weekly frequency with time period from 2010 to 2019 and can be found on finance. yahoo.com/. One of the series is the stock price of American Airlines while the two others are currency rates of American Dollars with Canadian Dollars and Brazilian Real:

- American Airlines Group Inc. (AAL)
- USD/CAD (CAD=X)

## • USD/BRL (BRL=X)

Once the series are chosen, the first step of the method-065 ology was to develop a Time Series Analysis procedure, in order to gain information about each of them. With this 067 analysis the goal was to gather information regarding seasonality, stationarity, trend, missing values and the number of differentiation needed to obtain a stationary behaviour. The results of this analysis is expressed on the table below. 071

	Trend	Statio	NumDiff	Season
ALL	Yes	No	1	No
USD/CAD	Yes	No	1	No
USD/BRL	Yes	No	1	No

In order to determine stationarity two methods were used: first, a visual analysis of each series. The Ameri-080 can Airlines series, as shown in the image below, is clearly non stationary, for example, since it shows a clear trend over time and one can suspect that it's mean and variance are also not constant over time (*weak stationary, see [9]*). Further-084 more, a *Augmented Dickey Fuller Test [9]* was also done so that the non-stationary could be statistically shown.



Figure 1. American Airlines Original Stock Price Series (left) and 094 1 time differentiated Return Series (right) 095

Even though the series have different behaviour over097 time, with respect to the analysis of interest all of them have098 identical results. With respect to the *NumDiff*, all of the se-099 ries needed to be discretely differentiated one time to gain100 stationary behaviour and pass the *ADF Test*.

Once the analysis is complete, the next step was to im-102 plement each of the following methods for time series fore-103 cast:

- 1. ARIMA 105
- 2. ARIMA + GARCH

- 3. Random Forest Regressor
- 4. Support Vector Machine Regressor
- 5. Multi Layer Perceptron Neural Networks
- 6. Recurrence Neural Networks
- 7. Facebook Prophet Model

Each of the methods will be briefly explained in the following paragraphs, however the results are clustered together in the end of this section in the tables 2 and 2.

#### ARIMA and GARCH

The first methods to be implemented are classic linear models for time series forecasting, the Auto Regressive Integrated Moving Average Model and the Generalized Autoregressive Conditional Heteroskedasticity.

The first in constructed with 2 simpler models, the AR (Auto Regressive) and MA (Moving Average), which equations are shown below. This model claims that the present value of the series is linear dependent of the past values until a lag-p in the past as well as in the linear combination of the errors until a lag-q past value. In order to determine the number of past values to use in the model, one can use the Autocorrelation and Partial Autocorrelation Functions, as describer in [9] and shown below. The *Integrated* part of the name suggests the number of differentiation needed to gain stationary behaviour, since this is a requisite for the model itself.

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i r y_{t-i} + \alpha_t + \sum_{i=1}^{q} \theta_i \alpha_{t-i}$$
 (1)

where  $y_t$  is the value of the time series in time step t and  $\alpha_t$  is a white noise series.

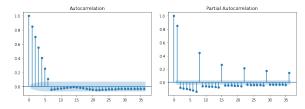


Figure 2. ACF and PACF American Airlines Stationary Series

The Garch model is used to describe the volatility (the variance) of the time series and it can integrate the ARIMA model by modeling the  $\alpha_t$  white noise (error). The equation that defines a GARCH(m,s) is as follows:

$$\alpha_t = \sigma_t \epsilon_t, \, \sigma_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i \alpha_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2$$
 (2)

#### Random Forests

As known, a Random Forest is an ensemble method implemented with a collection of Decision Trees [2]. Although known better for classification, Decision Trees, and
Random Forest, can be used for regression problems as
well.

For a regression problem, each Decision Tree is contructed in a similar way that it would be in a classification
problem. Given an tabular input shaped as a *moving win-*dow, each feature is used to determine the best split based
on the target value  $y_{t+1}$ . Once the best splits are determined
and the tree is constructed, given a new input, the value of
the prediction will be the average of the leaf values this new
input reaches. See [4] and [5].

With respect to the moving window approach, as well 178 as the other input format needed for each model, see 179 the subsection **Input Formats** in the end of the model's 180 introduction.

This model, as well as MLP, SVM AND Prophet were 183 implemented with hyperparameters search. RNN were not 184 because of the long training time and ARIMA/GARCH do 185 not have hyperparameters.

## **Support Vector Machines**

SVMs for regression are implemented in a analogous<sub>190</sub> way to classification SVMs. The regressor tries to fit the<sub>191</sub> best line *hyperplane* within a predefined threshold error<sub>192</sub> value *decision boundaries*. Instead of using the hyperplane<sub>193</sub> to separate different classes, the *SVM Regressor* uses it to<sub>194</sub> fit the behaviour of the time series. See [6].

## **Multi Layer Perceptrons**

The MLP Networks for regression and classification 199 are implemented and trained in the exact same way.200 The only difference is that the output layer, instead of 201 being composed of n nodes representing n classes, it is 202 made of a single node, which represents the predicted 203 value  $y_{t+1}$  of the series. With that value in hand, the 204 network uses back propagation and gradient descent to 205 find the best weight for its connections, as it is done 206 with a classification network. The input layer is made 207 of the l past values of the series and, for this project, l=12.208

#### **Recurrent Neural Networks**

A recurrent neural network(RNN) is a type of artificial212 neural network commonly used in speech recognition and213 natural language processing. Recurrent neural networks214 recognize data's sequential characteristics and use patterns215

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to predict the next likely scenario. RNNs are distinct from other types of artificial neural networks because they use feedback loops to process a sequence of data that that informs the final output. These feedback loops allow information to persist.

The RNN processes the sequence of vectors one by one. While processing, it passes the previous hidden state to the next step of the sequence. The hidden states act as the neural network's memory, which holds information on previous data the network has seen before. Then the input and previous hidden state are combined to form a vector. The vector then goes through the activation which decides what to do with the data, and the output is the new hidden state.

Long short-term memory (LSTM) is an artificial recurrent neural network(RNN) architecture. LSTMs were created as the solution to vanishing gradient problem due to short-term memory. In this project, we used a Vanilla LSTM, which is an LSTM model that has a single hidden layer of LSTM units, and an output layer used to get one prediction value yt+1. The ni is the number of the time steps for one LSTM cell/unit, and nf is the is the number of features which is 1 since we are working with univariate time series. Choosing a right value of ni would avoid you from overfitting with short amount of data and getting explosive predict value. u is the unit number of LSTM and e is the epochs. The bigger the u and e are, and the more data are used to train and fit model. To demonstrate the model, a batch which contains the value of the end of the training data series which has the same length with test series are used to predict the first value in the test series. Then the prediction is added into the end of current batch and also into an array to store all the prediction, and the first value was removed. The batch will be full of predictions, and the information in the batch will be still used to get new predictions until the array was the same length as the test series. Then get the error by comparing the test series and the prediction array. See[1] and [3].

#### **Prophet**

The Prophet is a Facebook Open Source project for time series predictions based on an additive model that tries to sum together 3 different functions that tries to model trend g(t), seasonality s(t) and holiday/weekend effects h(t). See [8] and [7].

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{3}$$

The Trend model, g(t), can be implemented in two different ways, according to [8]. First, there is a model that assumes a linear growth over time without a saturation point.

Secondly, there is a non linear growth with a carrying ca-270 pacity as saturation point. The equations that define these models are, respectively:

$$g(t) = (k + a(t)^{T} \delta)t + (m + a(t)^{T} \gamma)$$

$$g(t) = \frac{C}{1 + exp(-k(t - m))}$$
(4)275
(5)277

where k is the growth rate,  $\delta$  has the rate adjustment,  $m^{279}$  is the offset parameter,  $\gamma$  is a variable to make the function continuous and C is the carrying capacity.

The seasonality model is, basically, a Fourier Series that 282 captures the periodic behaviour of the seasonal model. 283

$$s(t) = \sum_{n=1}^{N} \left( \alpha_n cos\left(\frac{2\pi nt}{P}\right) + \beta_n sin\left(\frac{2\pi nt}{P}\right) \right)$$
(6)<sup>286</sup><sub>287</sub>

At last, the holidays/weekend model is implemented 289 with a auxiliary table that list all the holidays and events. 290 This table is used to add an indicator functions that tells if a 291 time step t occurs during a holiday i and assign a parameter 292 for each holiday which is the corresponding change in the 293 forecast [8]. Note that the holiday model is not of large 294 importance for this project since the frequency of the time 295 series is weekly and the table presented above was not 296 implemented.

## **Input Formats**

The models implemented in this project needed two301 types of input formats, that is, two different ways to reshape302 the time series in order to implement the algorithms.

First, for ARIMA, GARCH, RNN and Prophet, the series<sub>304</sub> were passed as input as the were originally, a pandas series<sub>305</sub> which is, basically, a list with the values of the series at each<sub>306</sub> time step. Sometimes, instead of a pandas series, a pandas<sub>307</sub> dataframe was needed so that the model had the data of each<sub>308</sub> observation as index.

For *Random Forests*, *SVM* and *MLP* the series were re-310 shaped into a moving window table. That means a original<sub>311</sub> series with the format  $[y_0, y_1, y_2, ..., y_t]$  was reshaped into<sub>312</sub> the following table:

Past Steps			$Y_{-}\{t\}$	$Y_{t+1}$	
$y_0$	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$
$y_{t-5}$	$y_4$	$y_{t-3}$	$y_{t-2}$	$y_{t-1}$	$y_t$

Each row is a window of the time series and the last321 column will be used as "target" for the supervised learning322 algorithms. Note that, from row i to row i+1 thee window323

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is shifted one unit to the right. The  $Y_{t+1}$  column is used as target while the others are passed as features/inputs.

#### **RMSE Tables**

American Series Training RMSE			
Method	Statio	Non-statio	
ARIMA	0.0880	X	
GARCH	0.0880	X	
RF	0.0487	0.0013	
SVM	0.0609	0.0725	
MLP	0.0577	0.0102	
RNN	X	X	
Prophet	0.1253	0.0431	

American Series Forecasting RMSE			
Method	Statio	Non-statio	
ARIMA	0.1534	X	
GARCH	0.1534	X	
RF	0.0539	0.0099	
SVM	0.0730	0.0965	
MLP	0.0648	0.0050	
RNN	X	3.7608	
Prophet	0.0920	0.0758	

## 3. Conclusions

Once the RMSE for all of the models and series are computed and compared, there are, at least, five conclusions one could make:

- For stationary series, the classic approach produces good results when compared to machine learning models
- Random Forest produced some of the smallest error rates for all series, stationary or not.
- 3. The models for non stationary series produced better errors than the ones for stationary series.
- 4. MLP produced the **best forecast** for all 3 non-stationary series.
- 5. The Prophet did not perform well for any of the series.

There may be a reason for the results of the Prophet: the series chosen for this project have weekly frequency and do not have the holidays table as well, so the additive model that Prophet implements may not have being adequate for this time series.

The RNN results were specially interesting however, once again there might be a reason: since the hyperparameter search was implemented by *hard coding* for this model

and, because of the enormous amount of training time, there 378 is no guarantee that the best, or even a good, choice of hyperparameters was found.

At last, there is enough evidence to answer the main 381 question of this project: are Neural Networks the best 382 model for time series forecasting?. Not necessarily! 383 The MLP has the best results for non stationary series, 384 but the Random Forest displayed comparable RMSE and ARIMA/GARCH, for two of the stationary series, have also 386 shown great errors.

## References

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- [7] Facebook Prophet Project. Prophet: Forecasting at scale.405 https://facebook.github.io/prophet/. 3 406
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## A. Helpful Instructions

This project contains a *README.md* file with **all** the in413
structions needed to understand the structure of the project's
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directories and files.

In order to see the same images for the remaining series, refer to *img directory* in the main directory of this project.

In order to see the all the jupyter notebooks implemented for this project, refer to *code directory* in the main directory of this project.

The *ref directory* has some of the bibliography used during the project and *data directory* has the time series in *csv* 423 files.

# B. Images and Results of remaining Time Se-426 ries 427

This section, although optional for the reader, gives, first, 428 the RMSE Tables for the two remaining time series and the 429 images of all training and forecasts each series.

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USD CAD Series Training RMSE		
Method	Statio	Non-statio
ARIMA	0.0001	X
GARCH	0.0001	X
RF	0.0475	0.0016
SVM	0.0604	0.0421
MLP	0.0548	0.0088
RNN	X	X
Prophet	0.1205	0.0440

USD CAD Series Forecasting RMSE			
Method	Statio	Non-statio	
ARIMA	0.0011	X	
GARCH	0.0011	X	
RF	0.0547	0.0079	
SVM	0.0586	0.0463	
MLP	0.0538	0.0043	
RNN	X	0.0267	
Prophet	0.1004	0.1302	

USD BRL Series Training RMSE			
Method	Statio	Non-statio	
ARIMA	0.0042	X	
GARCH	0.0042	X	
RF	0.0357	0.00087	
SVM	0.0448	0.0734	
MLP	0.0420	0.0066	
RNN	X	X	
Prophet	0.0895	0.0377	

USD BRL Series Forecasting RMSE		
Method	Statio	Non-statio
ARIMA	0.0031	X
GARCH	0.0031	X
RF	0.0687	0.0080
SVM	0.0794	0.1038
MLP	0.0863	0.0063
RNN	X	0.0944
Prophet	0.1605	0.0912

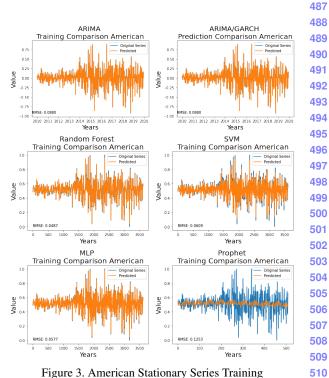


Figure 3. American Stationary Series Training

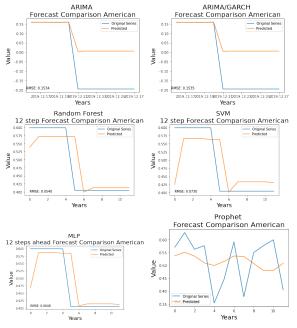


Figure 4. American Stationary Series Forecast

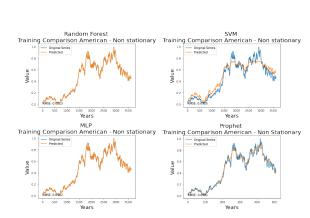


Figure 5. American Original Series Training

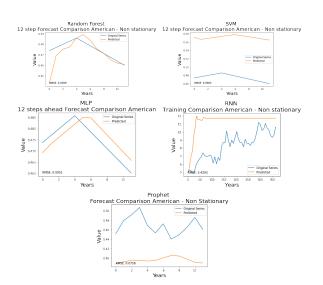


Figure 6. American Original Series Forecast

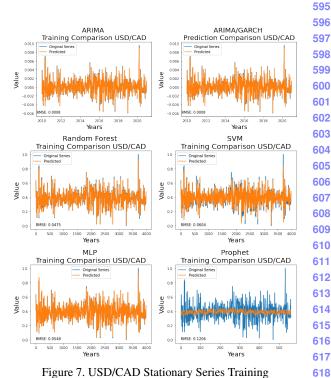


Figure 7. USD/CAD Stationary Series Training

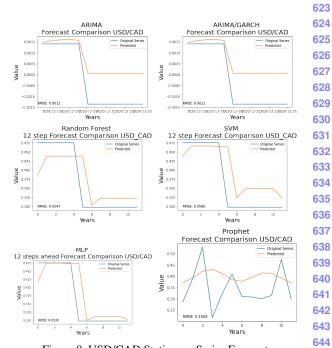


Figure 8. USD/CAD Stationary Series Forecast

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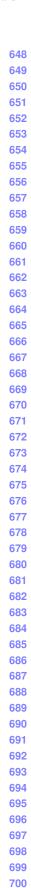
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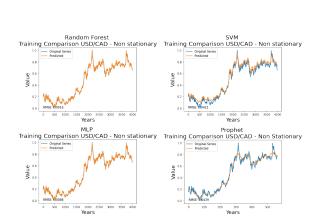


Figure 9. USD/CAD Original Series Training

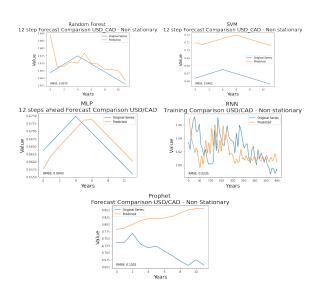


Figure 10. USD/CAD Original Series Forecast

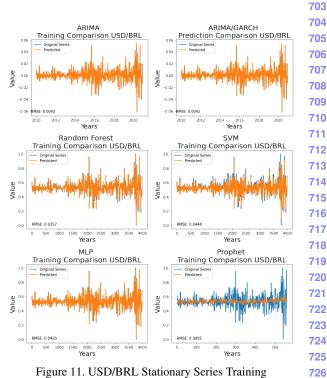


Figure 11. USD/BRL Stationary Series Training

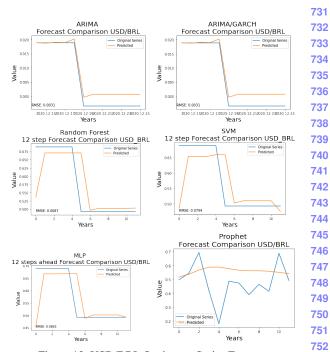


Figure 12. USD/BRL Stationary Series Forecast

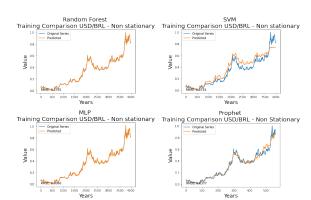


Figure 13. USD/BRL Original Series Training

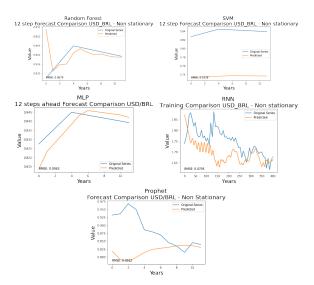


Figure 14. USD/BRL Original Series Forecast