Time Series Forecasts

ICMS tax collection

Guttenberg Ferreira Passos

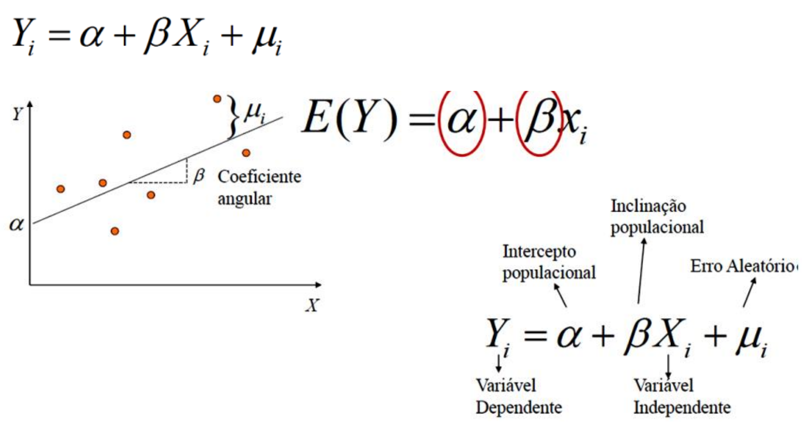
This article aims to make the ICMS tax collection forecast considering linear and non-linear models with time series.

- Statistics with Trend Analysis were used for linear models;
- Statistical Methods, Artificial Intelligence, Machine Learning and Deep Learning were used for non-linear models, through the following algorithms:
  - Naive;
  - Exponential Smoothing;
  - ARMA - Autoregressive Moving Average;
  - ARIMA - Autoregressive Integrated Moving Average;
  - SARIMAX – Seasonal Autoregressive Integrated Moving Average;
  - DeepAR – GluonTS - Probabilistic Time Series Modeling;
  - MLP - Multilayer Perceptron;
  - LSTM - Long short-term memory.

Trend Analysis is an aspect of business analysis that attempts to predict the future movement of a product or service based on historical and statistical data. With this, it is possible to define action strategies, action plans and decision making.

One of these trends is Regression Analysis, which studies the relationship between a dependent variable and other independent variables. The relationship between them is represented by a mathematical model. This model is called the Simple Linear Regression Model (MRLS), which defines a linear relationship between the dependent variable and an independent variable.

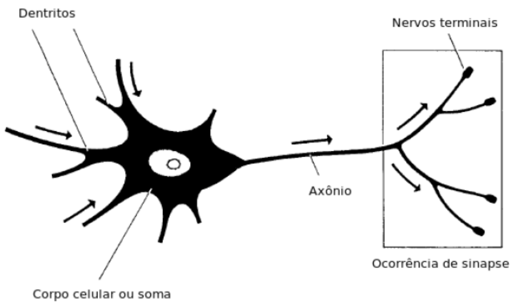
MRLS Simple Linear Regression Model:



Biological Neuron

The Deep Learning Book Brazil is a [Data Science Academy] initiative with the objective of helping to spread Deep Learning, one of the most revolutionary technologies of our time used in the construction of Artificial Intelligence applications.

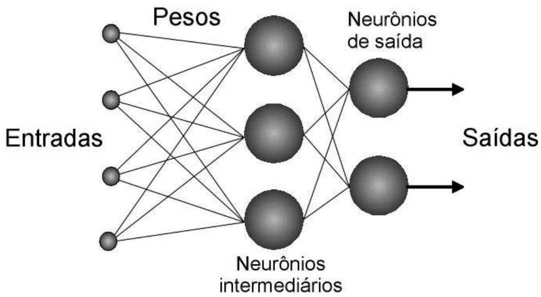
According to the Deep Learning Book, the biological neuron is a cell, which can be divided into three sections: the cell body, the dendrites and the axon, each with specific but complementary functions.



Source: Data Science Academy - DSA

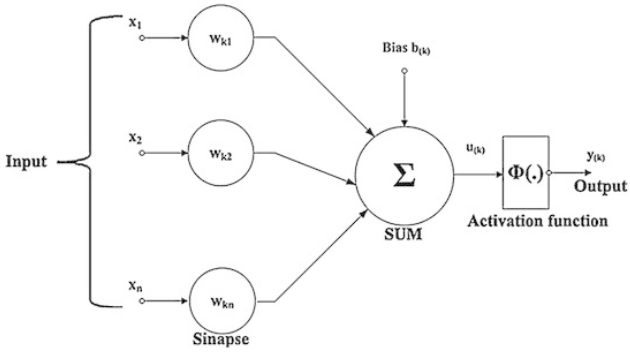
Artificial Neuron

An artificial neuron represents the basis of an Artificial Neural Network (ANN), a model of neuroinformatics oriented to biological neural networks.



Source: Data Science Academy - DSA

The knowledge of an ANN is encoded in the structure of the network, where the connections (synapses) between the units (neurons) that compose it are highlighted.



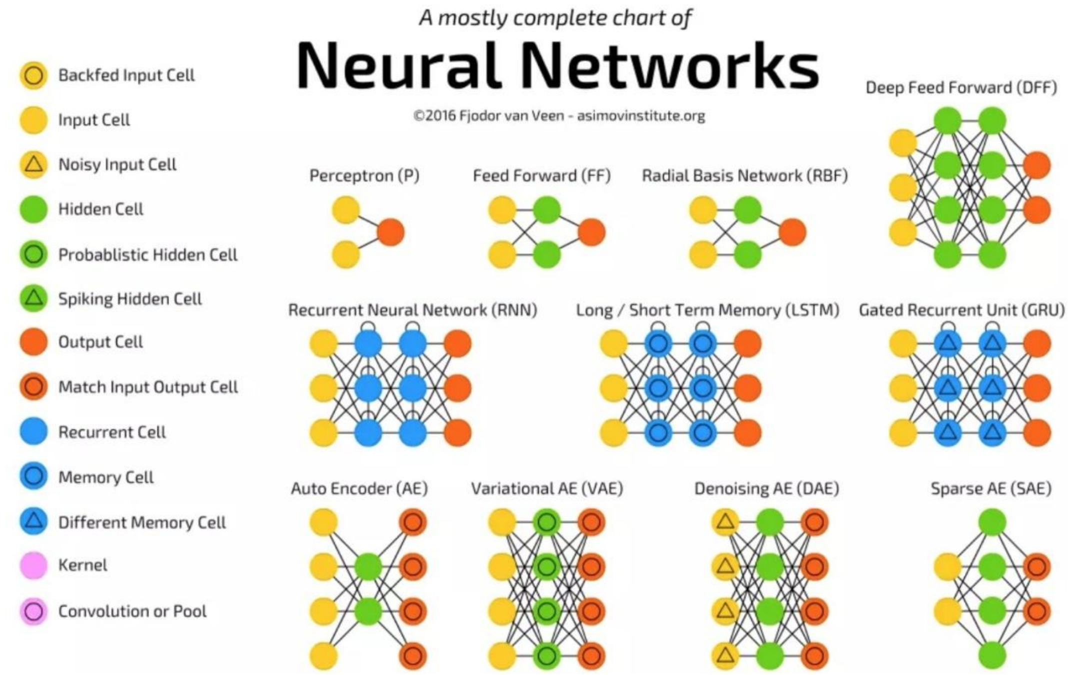
Source: Data Science Academy - DSA

In machine learning, Perceptron is a supervised learning algorithm of binary classifiers. A binary classifier is a function that can decide whether or not an input, represented by a vector of numbers, belongs to some specific class. It is a type of linear classifier, that is, a classification algorithm that makes its predictions based on a linear predictor function by combining a set of weights with the vector of features.

Neural Networks

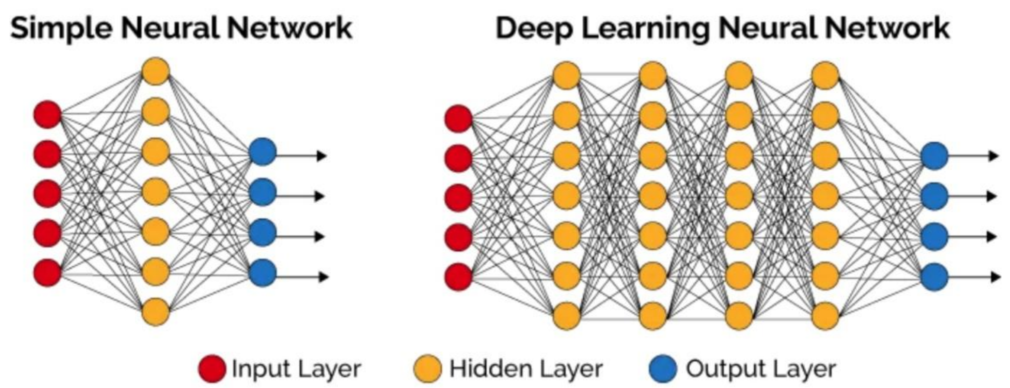
Neural networks are computing systems with interconnected nodes that function like neurons in the human brain. Using algorithms, they can recognize hidden patterns and correlations in raw data, group and classify them, and over time continually learn and improve.

Asimov Institute https://www.asimovinstitute.org/neural-network-zoo/ has published a cheat sheet containing various neural network architectures, we will concentrate on the architectures below focusing on Perceptron(P), Feed Forward (FF), Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM):



Source: THE ASIMOV INSTITUTE

Deep learning is one of the foundations of Artificial Intelligence, a type of Machine Learning that trains computers to perform tasks like humans, which includes speech recognition, image identification and predictions, learning over time. We can say that it is a Neural Network with several hidden layers:



Base Model

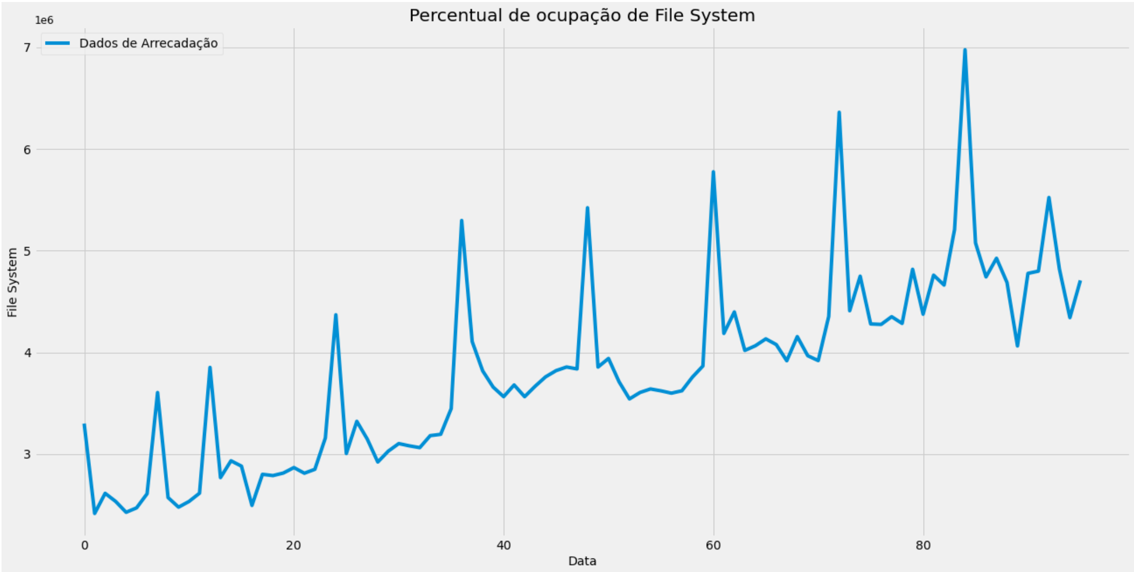
Business Problem Definition

ICMS tax collection forecast.

Data set

We use datasets that show ICMS collection. The data has records from the years 2010 to 2015.

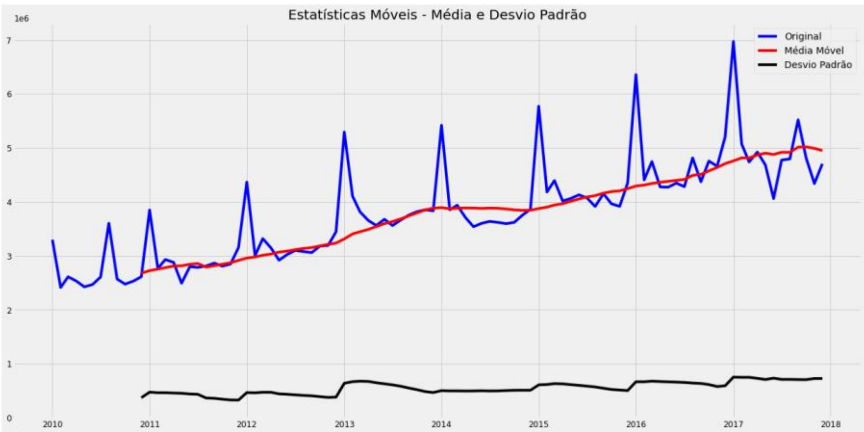
Database with 1 dataset with 2 columns, date and ICMS collection, with 96 records:



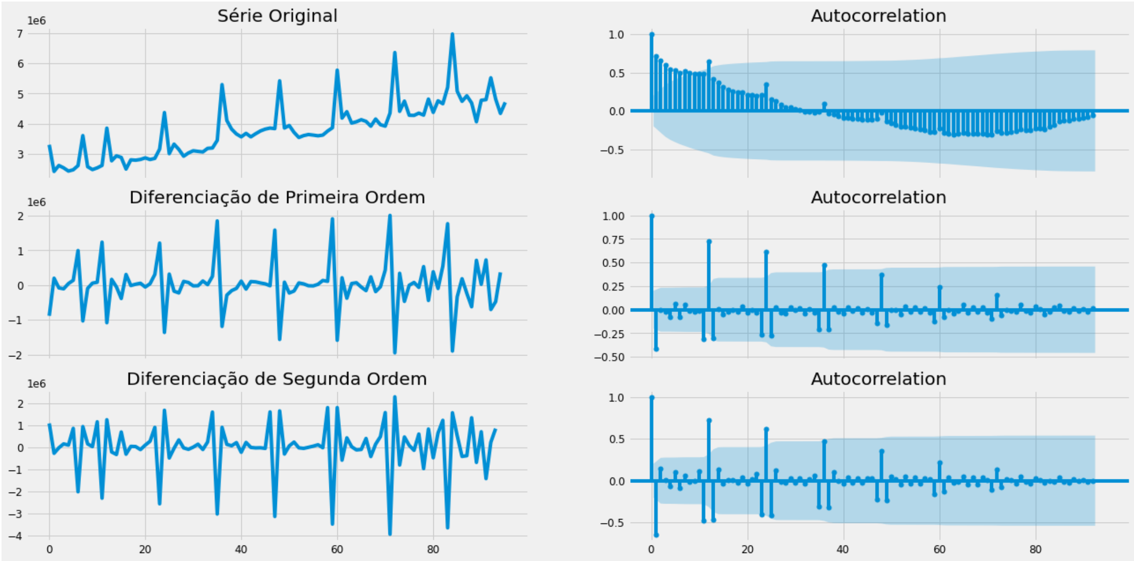
We noticed that there is a trend of increasing ICMS collection over time.

Exploratory Data Analysis

Let's test the stationarity of the series.



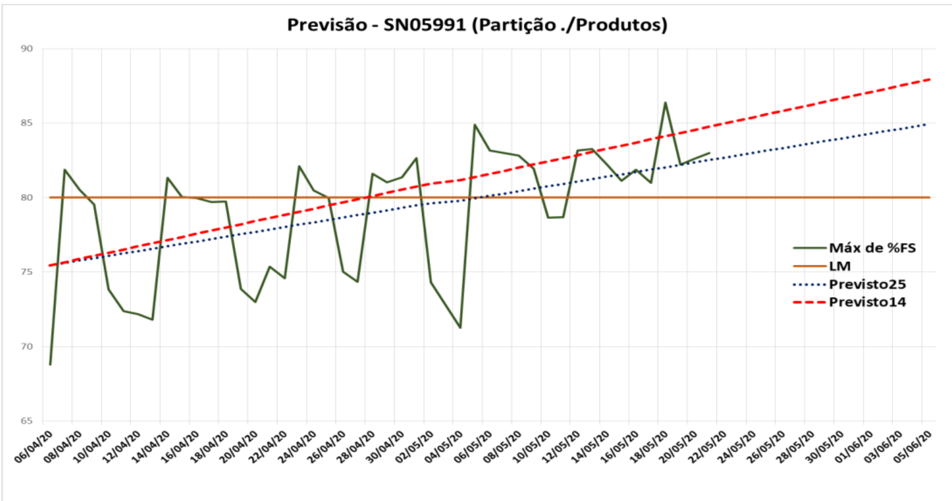
The ACF graph allows the evaluation of the minimum differentiation necessary to obtain a stationary series (Parameter d for the ARIMA Model):



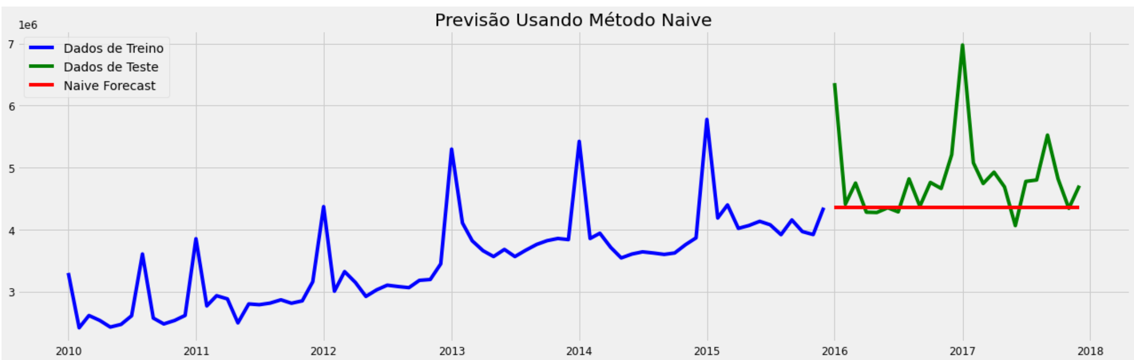
To run the models using Statistical Methods, the data were separated into:

- 72 training records and
- 24 validation records.

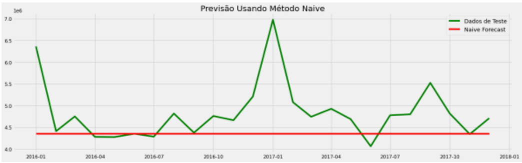
Model 01 - Predictions Simple Linear Regression Method MRLS



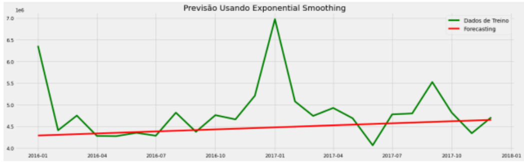
Model 11 - Naive Method Forecasts



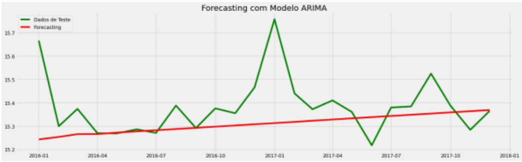
11 – Naive Method



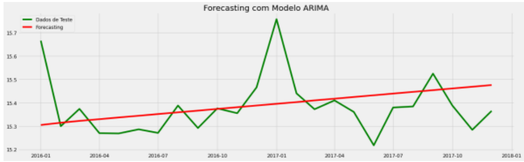
12 – Exponential Smoothing



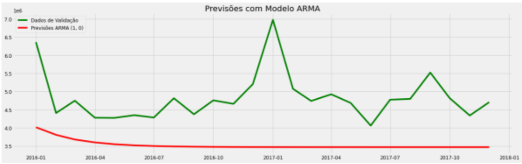
13 - Forecasting – ARIMA LOG (2, 1, 0)



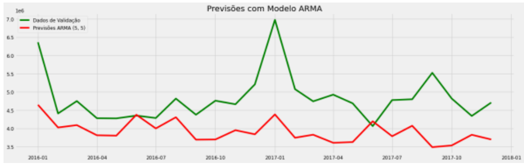
14 - Forecasting – ARIMA LOG (1, 1, 1)



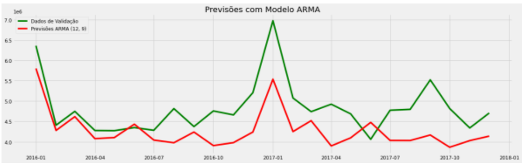
15 – ARMA (1, 0)



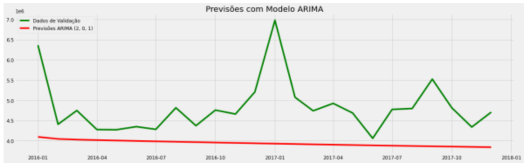
15 – ARMA (5, 5)



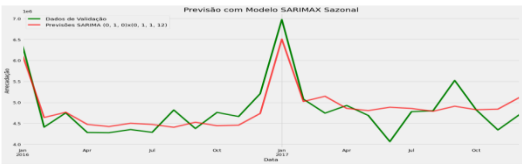
15 – ARMA (12, 9)



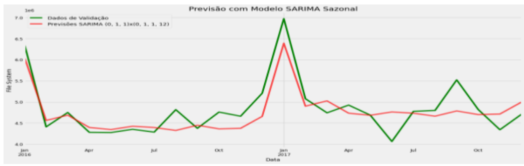
16 - Predict - ARIMA (2, 0, 1)



17 – SARIMAX (0,1,0)(0,1,1,12)



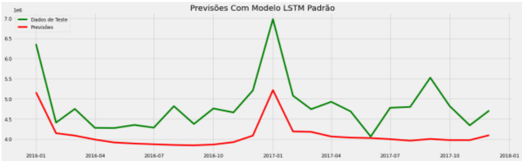
18 – SARIMAX (0,1,1)(1,1,1,12)



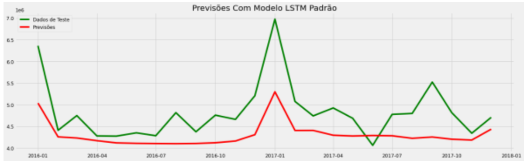
Models using:

Inteligência Artificial - IA

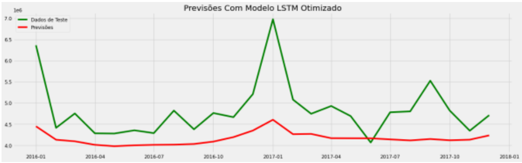
22 – LSTM - IA (5 repetitions)



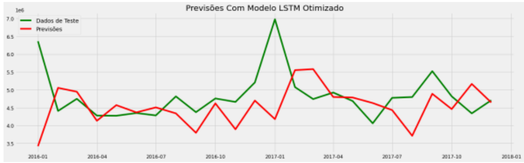
22 – LSTM - IA (20 repetitions)



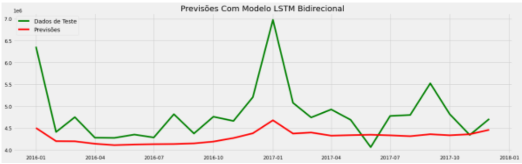
23 – Optimized LSTM - IA



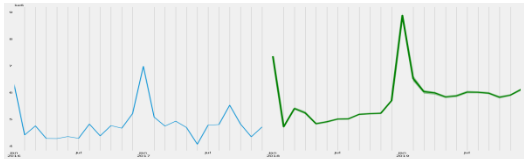
24 – Stacked LSTM - IA



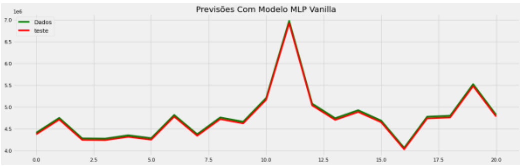
25 – LSTM Bidirectional – IA



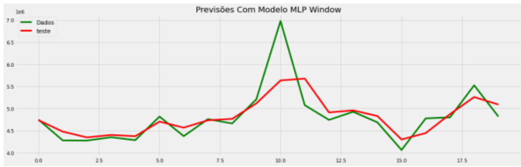
25 – DeepAR – IA



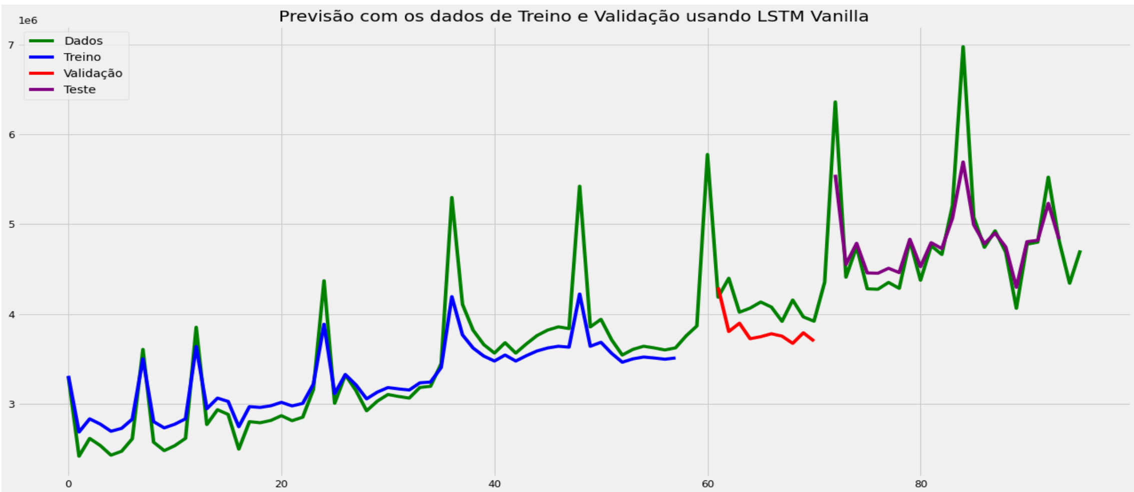
RNN01 – MLP Vanilla – IA –



RNN01 – MLP Window – IA –

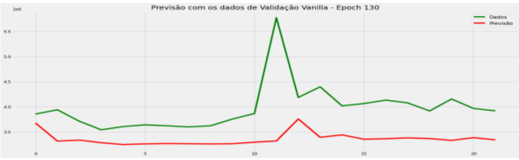


Predictions using Artificial Intelligence - AI - Deep Learning



RNN02 – LSTM Vanilla IA – Validation

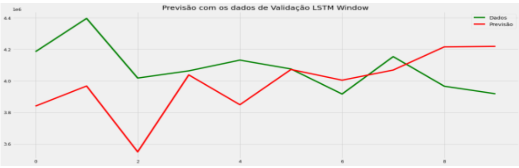
Epoch = 130 - avoid the Overfitting



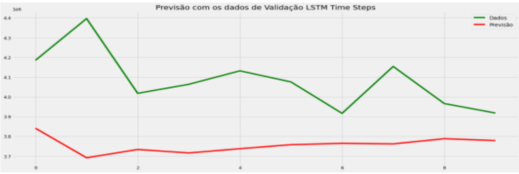
RNN02 – LSTM Vanilla IA – Validation

Epoch = 200

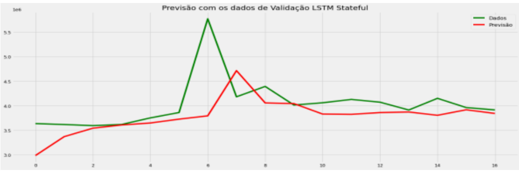
RNN02 – LSTM Window IA– Validation



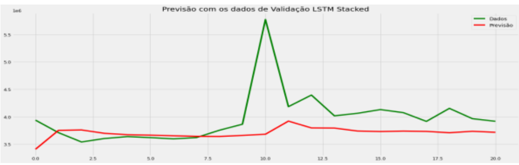
RNN02–LSTM Time Steps IA Validation



RNN02 – LSTM Stateful IA – Validation

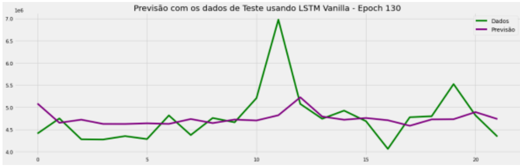


RNN02 – LSTM Stacked IA – Validation



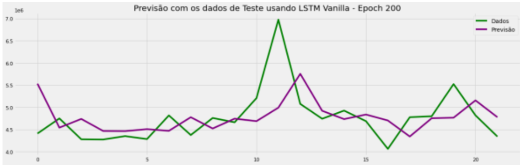
RNN02 – LSTM Vanilla IA – Test

Epoch = 130 - avoid the Overfitting

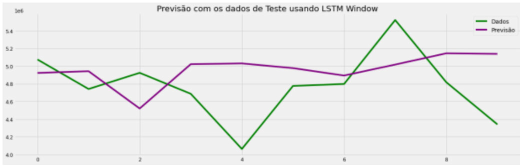


RNN02 – LSTM Vanilla IA – Test

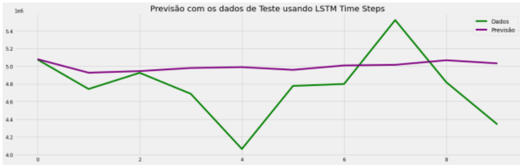
Epoch = 200



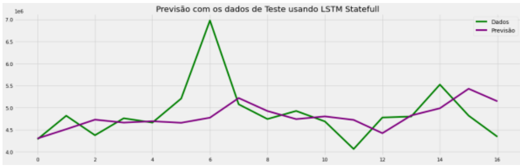
RNN02 – LSTM Window IA – Test



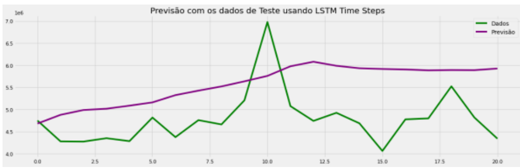
RNN02 – LSTM Time Steps IA – Test



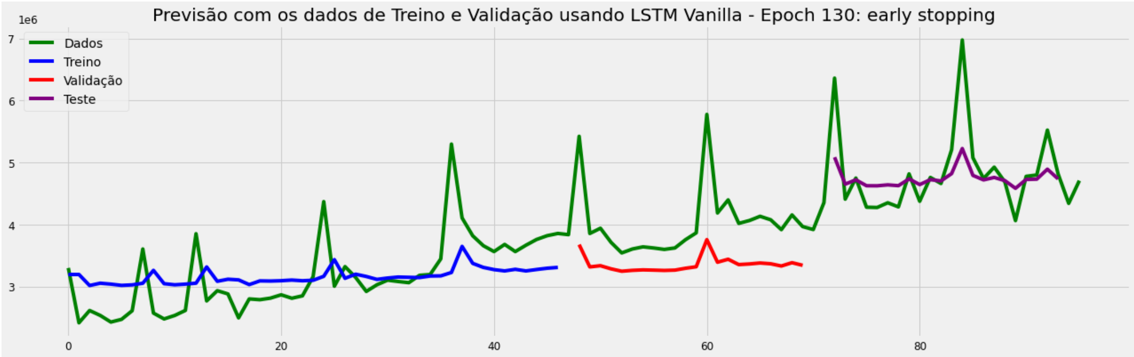
RNN02 – LSTM Stateful IA – Test



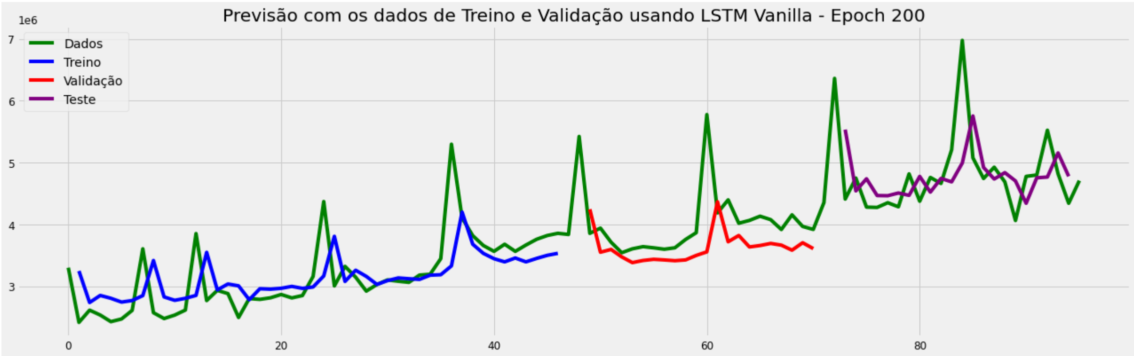
RNN02 – LSTM Stacked IA – Test



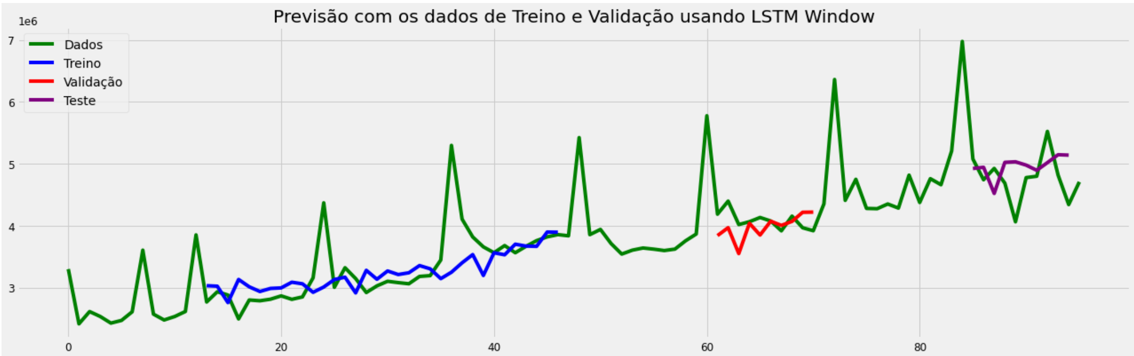
Model RNN02 – LSTM Vanilla IA – Epoch = 130 – avoid the Overfitting



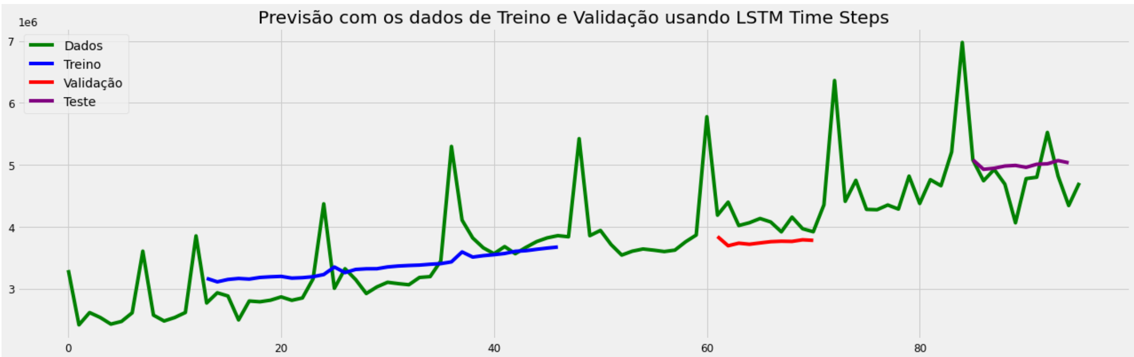
Model RNN02 – LSTM Vanilla IA – Epoch = 200



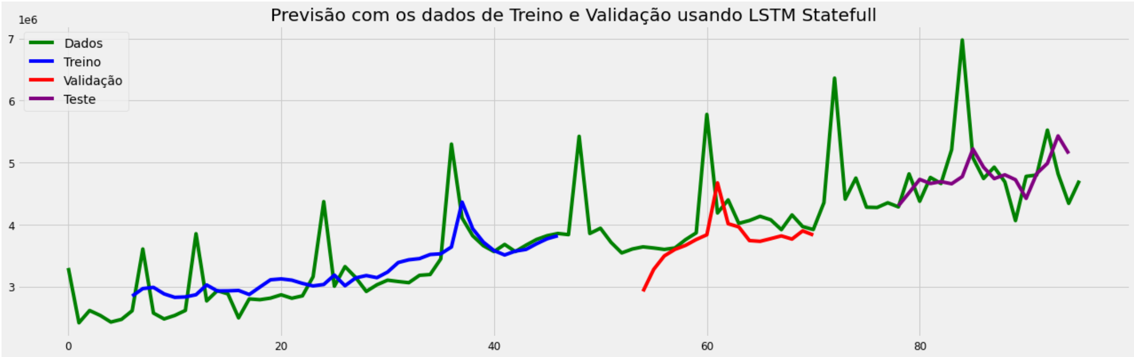
Model RNN02 – LSTM Window IA



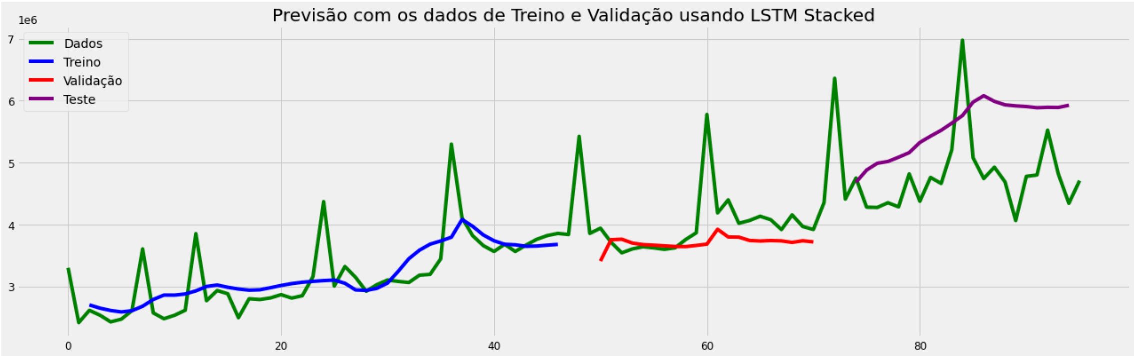
Model RNN02– LSTM Time Steps



Model RNN02– LSTM Stateful

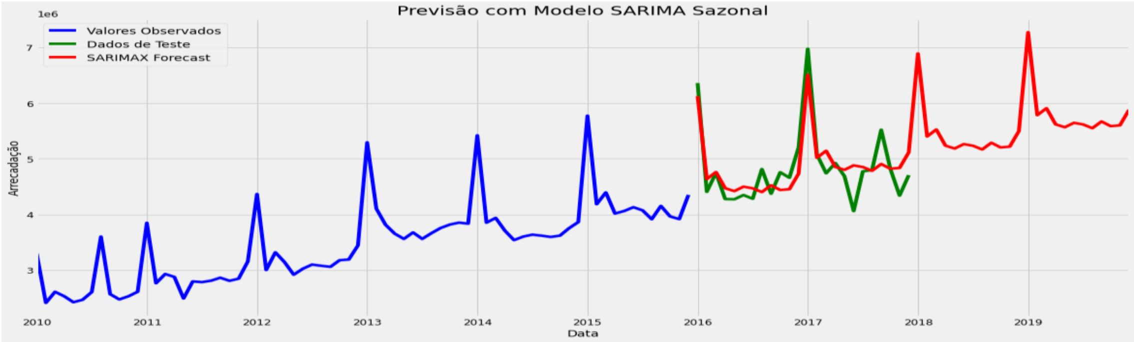


Model RNN02– LSTM Stacked

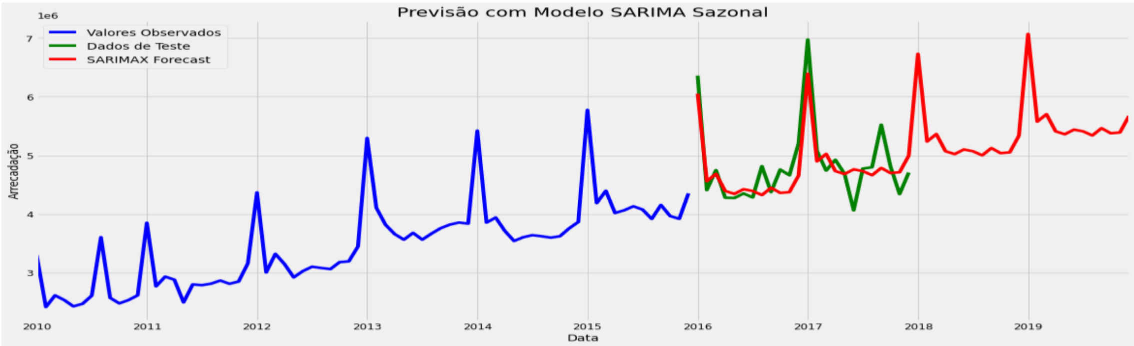


Forecasting using Artificial Intelligence - AI

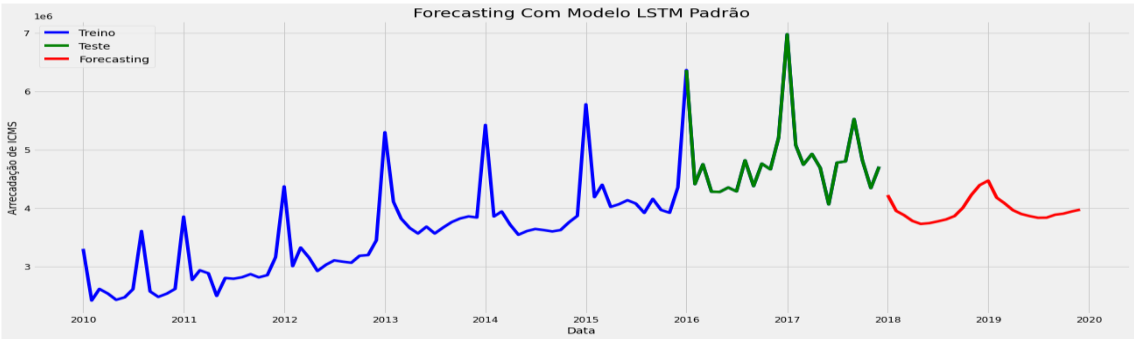
Model 17 – SARIMAX (0,1,0)(0,1,1,12)



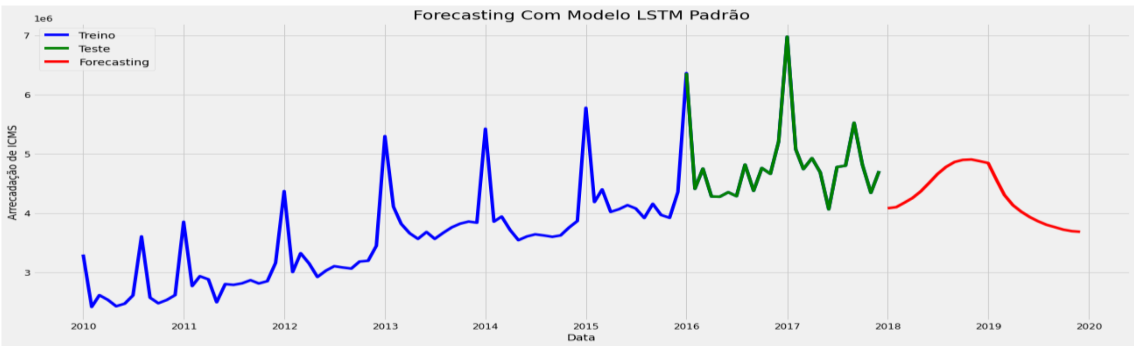
Model 18 – SARIMAX (1,0,1)(1,1,1,12)



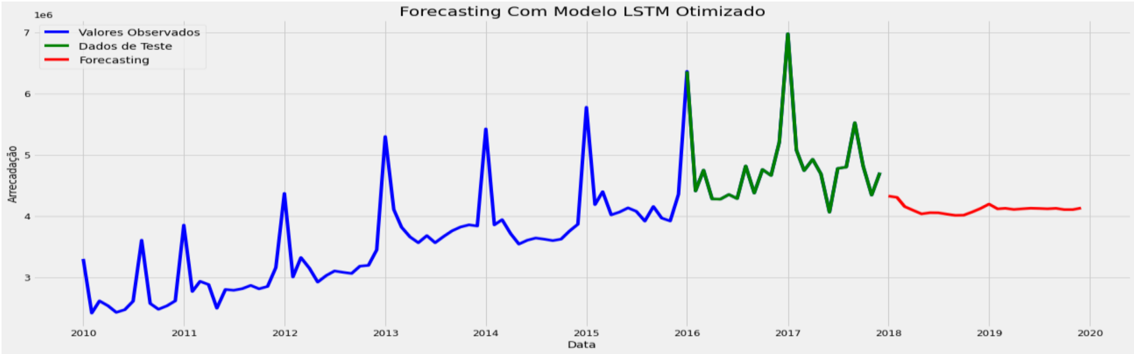
Model 22 – LSTM - IA (5 repetitions)



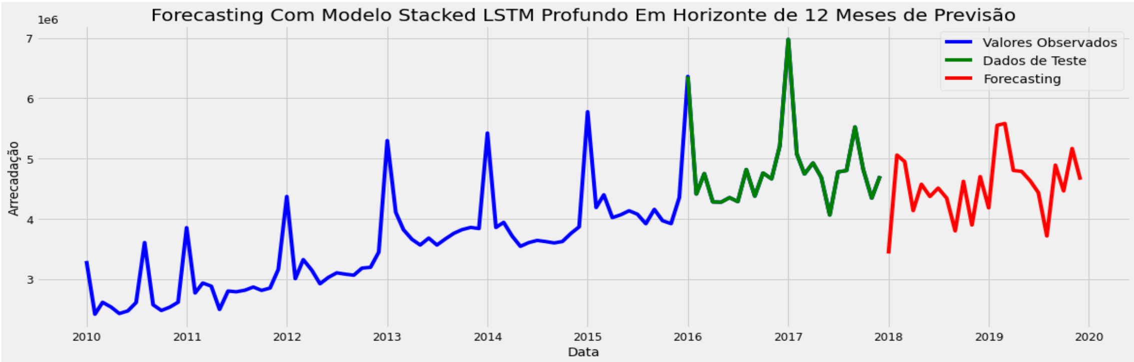
Model 22 – LSTM - IA (20 repetitions)



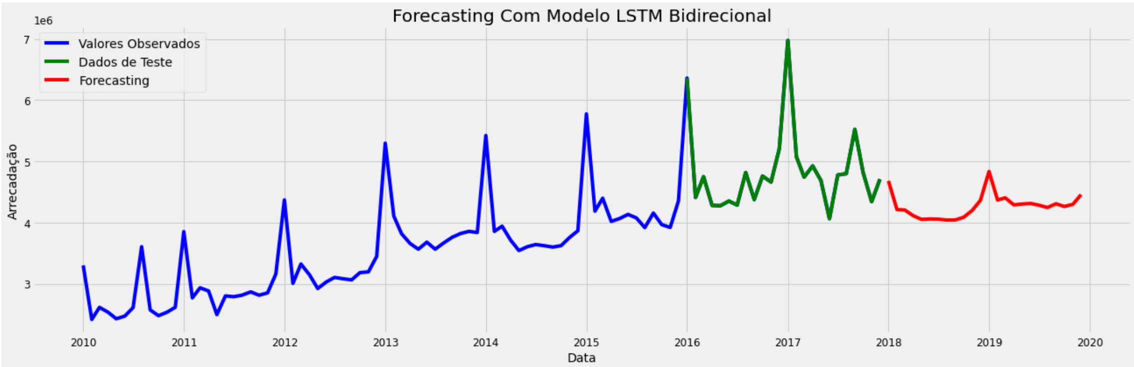
Model 23 – Optimized LSTM - IA



Model 24 – Stacked LSTM - IA



Model 25 – LSTM Bidirectional – IA



Model Results:

				RSME	RSME	RSME
Nº	Arquitetura	Modelo	Setup	treino	validação	teste
1	Métodos Estatísticos	BASE 11	Método Naive - p/ Mi			0,8054
2	Métodos Estatísticos	BASE 11	Método Naive - LOG			0,1551
3	Métodos Estatísticos	BASE 11	Método Naive			805471,0878
4	Métodos Estatísticos	Forecasting 12	Exponential Smoothing v1			857879,2406
5	Métodos Estatísticos	Forecasting 12	Exponential Smoothing v2			750397,7727
6	Métodos Estatísticos	ARIMA 13	ARIMA LOG (2, 1, 0)			767631,9506
7	Métodos Estatísticos	ARIMA 14	ARIMA LOG (1, 1, 1)			694827,8110
8	Métodos Estatísticos	ARMA 15	ARMA (1, 0)			1445179,5400
9	Métodos Estatísticos	ARMA 15	ARMA (5, 5)			1101078,9110
10	Métodos Estatísticos	ARMA 15	ARMA (12, 9)			706415,3914
11	Métodos Estatísticos	ARIMA 16	ARIMA (2, 0, 1)			1099391,396
12	Métodos Estatísticos	SARIMAX 17	SARIMAX (0, 1, 0) (0, 1, 1, 12)			332666,2626
13	Métodos Estatísticos	SARIMAX 18	SARIMAX (0, 1, 1) (0, 1, 1, 12)			336782,4202
14	IA - Deep Learning	LSTM 22	LSTM (5 repetições)			1037107,009
15	IA - Deep Learning	LSTM 22	LSTM (20 repetições)			878868,4191
16	IA - Deep Learning	LSTM 23	LSTM Otimizado			945778,1667
17	IA - Deep Learning	LSTM 24	Stacked LSTM			877490,6632
18	IA - Deep Learning	LSTM 25	LSTM Bidirecional			850832,6951
19	IA - Deep Learning	DeepAR 26	DeepAR			4874330,639
20	Inteligência Artificial - IA	RNA - MLP 1	MLP Vanilla	610423,2630		795393,9775
21	Inteligência Artificial - IA	RNA - MLP 2	MLP e Método Window	480295,7828		605733,0842
22	IA - Deep Learning	RNN - LSTM 1	LSTM Vanilla - 130 epochs	546148,5770	785606,6766	1417809,7913
23	IA - Deep Learning	RNN - LSTM 1	LSTM Vanilla - 200 epochs	496556,0484	586356,0493	950176,2755
24	IA - Deep Learning	RNN - LSTM 2	LSTM e Método Window	488946,9051	289236,3698	448340,4022
25	IA - Deep Learning	RNN - LSTM 3	LSTM e Time Steps	351787,0114	1184513,5124	1721690,0960
26	IA - Deep Learning	RNN - LSTM 4	LSTM e Stateful	444933,0519	549877,8552	911738,8182
27	IA - Deep Learning	RNN - LSTM 5	LSTM e Stacked	417403,4958	500538,7458	992971,6186

Model Architectures using AI

Model 22 – LSTM - IA (5 repetitions)

```
Número de repetições = 20
modelo_lstm.add(LSTM(50, activation = 'relu', input_shape = (n_input, n_features)))
modelo_lstm.add(Dropout(0.10))
modelo_lstm.add(Dense(100, activation = 'relu'))
modelo_lstm.add(Dense(100, activation = 'relu'))
modelo_lstm.add(Dense(1))
modelo_lstm.compile(optimizer = 'adam', loss = 'mean_squared_error')
monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3, patience=3, verbose=1, mode='auto')
modelo_lstm.fit_generator(generator, epochs = 200)
```

Model 23 – Optimized LSTM - IA

```
Número de repetições = 20
modelo_lstm.add(LSTM(40, activation = 'tanh', return_sequences = True, input_shape = (n_input, n_features)))
modelo_lstm.add(LSTM(40, activation = 'relu'))
modelo_lstm.add(Dense(50, activation = 'relu'))
modelo_lstm.add(Dense(50, activation = 'relu'))
modelo_lstm.add(Dense(1))
adam = optimizers.Adam(lr = 0.001)
modelo_lstm.compile(optimizer = adam, loss = 'mean_squared_error')
monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3, patience=5, verbose=1, mode='auto')
modelo_lstm.fit_generator(generator, epochs = 200)
```

Model 24 – Stacked LSTM - IA

```
modelo_lstm.add(LSTM(200, activation = 'relu', return_sequences = True, input_shape = (1, 1)))
modelo_lstm.add(LSTM(100, activation = 'relu', return_sequences = True))
modelo_lstm.add(LSTM(50, activation = 'relu', return_sequences = True))
modelo_lstm.add(LSTM(25, activation = 'relu'))
modelo_lstm.add(Dense(20, activation = 'relu'))
modelo_lstm.add(Dense(10, activation = 'relu'))
modelo_lstm.add(Dense(1))
modelo_lstm.compile(optimizer = 'adam', loss = 'mean_squared_error')
modelo_lstm.fit(X, y, epochs 5000, verbose = 1)
```

Model 25 – LSTM Bidirectional - IA

```
Número de repetições = 20
modelo_lstm.add(Bidirectional(LSTM(41, activation = 'relu'), input_shape = (41, 1)))
modelo_lstm.add(Dense(1))
modelo_lstm.compile(optimizer = 'adam', loss = 'mean_squared_error')
modelo_lstm.fit_generator(generator, epochs = 200)

lista_hiperparametros():
n_input = [24]
n_nodes = [100]
n_epochs = [200]
n_batch = [5]
n_diff = [12]
Número de repetições = 20
modelo_lstm.add(Bidirectional(LSTM(100, activation = 'relu'), input_shape = (41, 1)))
modelo_lstm.add(Dense(1))
modelo_lstm.compile(optimizer = 'adam', loss = 'mean_squared_error')
modelo_lstm.fit_generator(generator, epochs = 200)
```

Model Architectures using AI Deep Learning

Model RNN01 – MLP Vanilla – IA

```
model.add(Dense(8, input_dim = look_back, activation = 'relu'))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
model.fit(trainX, trainY, epochs = 200, batch_size = 2, verbose = 2)
```

Model RNN01 – MLP Vanilla – IA

```
model.add(LSTM(4, input_shape = (1, look_back)))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
model.fit(trainX, trainY, epochs = 200, batch_size = 1, verbose = 2)
```

Model RNN02 – LSTM Vanilla – IA

```
model.add(LSTM(4, input_shape = (1, look_back)))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
model.fit(trainX, trainY, epochs = 200, batch_size = 1, verbose = 2)
```

Model RNN02 – LSTM Window – IA

```
model.add(LSTM(4, input_shape = (1, look_back)))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
model.fit(trainX, trainY, epochs = 200, batch_size = 1, verbose = 2)
```

Model RNN02 – LSTM Time Steps – IA

```
model.add(LSTM(4, input_shape = (None, 1)))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
model.fit(trainX, trainY, epochs = 200, batch_size = 1, verbose = 2)
```

Model RNN02 – LSTM Stateful – IA

```
model.add(LSTM(4, batch_input_shape = (batch_size, look_back, 1), stateful = True))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
for i in range(200):
   model.fit(trainX, trainY, epochs = 1, batch_size = batch_size, verbose = 2, shuffle = False)
   model.reset_states()
```

Model RNN02 – LSTM Stacked – IA

```
model.add(LSTM(4, batch_input_shape = (batch_size, look_back, 1), stateful = True, return_sequences = True))
model.add(LSTM(4, batch_input_shape = (batch_size, look_back, 1), stateful = True))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
for i in range(200):
   model.fit(trainX, trainY, epochs = 1, batch_size = batch_size, verbose = 2, shuffle = False)
   model.reset_states()
```

The models were based on courses from the Data Science Academy DSA and the Community timeline on the portal: www.datascienceacademy.com.br