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Evaluating transfer learning for forecasting chikungunya cases

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In the last decade, we have seen a spread of chikungunya cases all over the country. Each year, new cities are reporting cases. To minimize the impact of this new disease on public health is necessary to understand how the disease spreads over time. It can be done using mathematical models[1]. Another approach is through statistical models, which can learn from historical data and can help us forecast the number of cases in the short to medium term. When it comes to forecasting, another class of model that is growing more common is deep learning models (DL)[2], which are quite robust at capturing the nonlinear associations between predictor variables and the response variable.

DL models are known to require large amounts of data to learn the association between the predictors and the number of cases. This makes using DL models for new diseases, such as chikungunya, a challenge. To work around this problem, we propose using transfer learning from dengue models.

Transfer learning is an artificial intelligence technique generally used in association with DL models, where a model that has been trained on an available data set is used to predict from a similar set of inputs coming from a different domain with minimal retraining and modifications to its architecture [3]. In our case, we used this technique to retrain a model trained in dengue data and use it to predict chikungunya data. This methodology is based on the fact that both arboviruses share common transmission modes and environmental forcing since the vector for both diseases is the mosquito Aedes aegypti.

In this paper, we applied transfer learning based on a Bi-directional LSTM (Bi-LSTM) model[4, 5]. The model is composed of two sequential layers with eight LSTM units each, intertwined with two 20%-dropout layers. The first LSTM layer is bidirectionally trained. The model was trained for 400 epochs with early stopping using a mean squared logarithmic error (MSLE) loss function and a Nesterov Adam optimizer. Besides helping to prevent overfitting during training the dropout layers were used in the prediction step to estimate confidence intervals for the predictions[6].

The model was trained to predict four weeks ahead of the last data point (wt+4). It uses four weeks of historical data to generate forecasts. Forecasts are done in a rolling window fashion, i.e. the historical data window is moved forward one week at-a-time, predicting the next 4 at each step. To train the model we used dengue incidence data from 2010 to 2023 from four Brazilian cities: Rio de Janeiro - RJ, Fortaleza - CE, Recife - PE, and João Pessoa - PB. The training datasets also include climate timeseries.

There are multiple ways to apply the transfer learning technique. In this work, we follow the transfer learning technique described in [7], which consists of using the weights of the model trained

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with dengue data to initialize a model that will be trained with chikungunya data. The Figure 1 summarize the workflow used.

To evaluate the performance of the model with the transfer learning technique, we adopted the associated skill score (SS) defined as $SS = 1 - \frac{RMSE_{model}}{RMSE_{reference}}$. Positive values of SS (smaller $RMSE_{model}$) mean the model's forecasts are better than reference, negative values of SS imply they are worse, and $SS = 0$ means both models perform equally. The reference is the same model without transfer learning, that is, the model trained on dengue and used to forecast chikungunya.

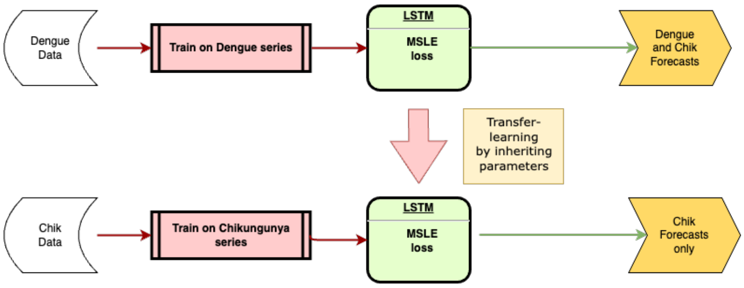

Figure 1: Workflow used to predict the chikungunya cases. Fonte: Autor (2023).

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