Nowcasting economic activity from Google Trends: a Deep Learning approach in post-pandemic times

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Abstract

Undoubtedly, Covid-19 is the perfect example of an exogenous shock, generating disruptive changes, as its impact, together with the deployment of government policies to prevent its propagation, has caused a sharp contraction in economic activity, the magnitude of which has yet to be determined, defying traditional economic forecasting tools. In this regard, this article contributes to the emerging literature on immediate GDP forecasting in advanced and emerging economies using artificial intelligence methods based on Google Trends data.

It then combines current forecasts obtained from a number of Deep Learning (DL) techniques to be defined below (LSTM, GRU, CNN, TCN, DMLP) y auto-encoder model, which are capable of handling high-dimensional information sets, capturing non-linear relationships and disruptive changes such as those caused by the pandemic.

Key word: Nowcast, Economic growth, Deep Learning (DL), emerging economies, time series forecasting; CNN; TCN; GRU; LSTM; Autoconder.

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1. Introduction

Today we live in a data-rich world. Statistical agencies, central banks, research institutes and private companies have access to thousands of economic and financial indicators. The extensive list of available data encompasses the famous term "Big Data", including sources such as internet search engines (Google Trends), cash register data, Google Analytics, social networks and much more. However, in the global economy, this wealth of information has not directly translated into faster and more accurate production of relevant economic statistics, such as Gross Domestic Product (GDP).

However, although we live in a data-rich world, statistical institutes publish economic indicators with colossal delays due to their internal cleaning and estimation process. For example, in the Colombian case, the GDP Colombia estimate provided by the statistical agency is published approximately 50 days after the end of the reference quarter.

In view of the above, a timely picture of the state of the economy is necessary. This is based on the fact that with relevant information it is possible to correct, slow down or boost the changes taking place in the economy, in order to direct them to desired thresholds. For example, the measure of Gross Domestic Product (GDP) is the main indicator of economic performance in both advanced and emerging economies. Even so, as mentioned above, measures such as GDP have considerable lags, which is why different monitoring and research bodies have increased the study of tools to bridge the information gap. Consequently, nowcasting has been the focus of a growing literature in recent years.

Regarding works related to real-time monitoring of economic conditions, the first ones are by (26), and (43). In these studies, the authors develop econometric frameworks with the aim of creating high-frequency indicators of economic activity. To summarise, the flash forecasting literature for monitoring the economy is interested in estimating existing economic indicators (usually quarterly GDP growth) in pseudo-real time by updating them.

Examples drawn from recent literature include the work of (9) and (12) for the United States; (23) for Argentina; (15), (27) and (5) for the Ecuadorian economy; the work of (16) for a set of Latin American economies; (13) for Turkey; among many others.

Nowcasting models are typically based on a wide range of data, such as consumer surveys, financial variables and macroeconomic indicators, and use factor models, bridging equations or large Bayesian vector auto-regressions to produce predictions of the variables of interest. Therefore, since a real-time"diagnosis of the economy is of vital importance, "nowcasting"has become popular. This term is a combination of now and forecasting (9).

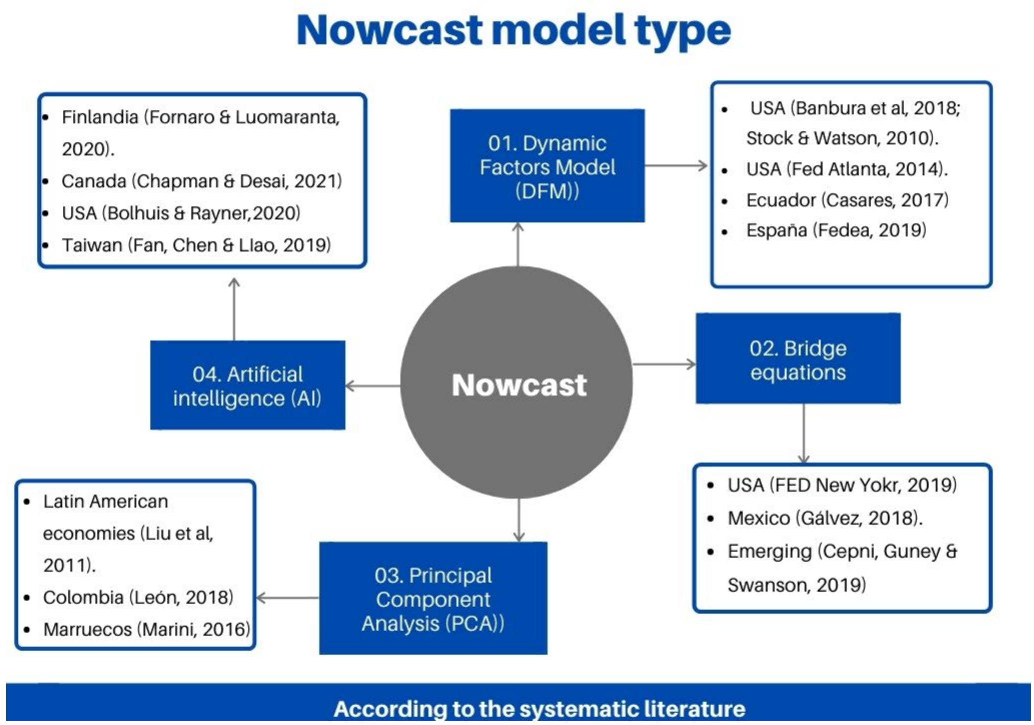
Forecasting is at the heart of decision making under uncertainty, thus Nowcasting can be defined as forecasting economic activity in the recent past, the present and the near future (44). Intuitively, specifications are estimated through Ordinary Least Squares (OLS) in which GDP is a function of its own lags, as well as of the contemporaneous and lagged values of the independent variables that are constructed from a set of monthly indicators (25).

2. Literature review

Generally, four types of models have been used for the development of nowcasting. Firstly, Dynamic Factor Models (DFM) such as the work of (26) which is one of the seminal works, those of (35) for Colombia with the use of transactions from the Banco de la República, that of (15) for Ecuador, those of the Atlanta Federal Reserve in the United States published on its website or those of Fedea for Spain. Secondly, the Bridge Equation (PE) models implemented by the Food and Agriculture Organization of the United Nations (FAO), the New York Federal Reserve, the Bank of England and, in general, most central banks in the world. In addition, the work of (16) does so for several Latin American countries. Thirdly, there are the Principal Component Analysis (PCA) models developed by (36) for emerging economies, such as those of (10) for Morocco and in general those along the lines of the International Monetary Fund (IMF) documents.

In the more modern literature we find nowcast models that venture into the field of artificial intelligence, specifically Machine Learning, such as the work of (46) for Lebanon, (13) for Turkey and (24) for Finland. For GDP Colombia we can find the NowCast of the Grupo Coyuntura Económica EAFIT. Furthermore, it is important to note that, in general, the literature combines the different approaches by making a comparative analysis, even using combinations between the different types of models. Figure 1 below presents a general outline summarising the range of models within flash forecasting.

Figure 1: **Nowcast model types**



Source: Own elaboration according to the systematic review of the literature.

Considering the set of possibilities, the paper will focus on combined dynamic factor models and deep learning (DL) models that are growing in the literature by leaps and bounds when it comes to time series projections in times of disruptive changes such as Covid-19. Our database will be Google Trends keywords in the selected country language that have high dynamic correlations with quarterly GDP.

Importantly, every time an internet user performs a search through a search engine, it is recorded in the database. There is work by (47) using Google trends to oil consumption trends and value forecasting and the experimental results outperformed other traditional statistical methods. Google Trends is a tool developed to record the keywords that Internet users search for. As the Internet becomes an indispensable part of modern daily life, the indication of keyword searches has become an important indicator for everyone to notice social, economic and technological developments. In addition, we can also observe public ideas, political concerns or economic growth by analysing changes in keyword searches. Also the work of (19) predicts building permits from Google Trends.

Many recent papers have investigated whether data from Internet search engines such as Google can help improve immediate predictions or short-term forecasts of macroeconomic variables.

The availability of search-able data on the Internet has provided a new resource for researchers interested in immediate forecasts or short-term forecasts of macroeconomic variables.

Pioneering articles such as Choi and Varian (2009, 2011) (17) have led to an explosion of immediate prediction work using Google data, including, among many others, Artola and Galan (2012)) (6), Askitas and Zimmermann (2009)) (7); (8), Nagao et al., (2019) (38); Among others.

A consensus can be reached from the literature. First, Google data are potentially useful in immediate forecasting or short-term forecasting, but there is little evidence that they can be used successfully for long-term forecasting. Second, Google data with an appropriate transformation is useful for broad macroeconomic variables (e.g. inflation, industrial production) and is more commonly used to forecast specific variables related to consumption, housing or labour markets.

2.1. Nowcast in post-pandemic times

Undoubtedly, Covid-19 is the perfect definition of an exogenous shock, which has generated disruptive changes, as its impact combined with the implementation of government policies to prevent its spread is causing a sharp contraction in economic activity, even the extent of production losses is yet to be determined, which has challenged traditional economic projection tools.

Thus, the interest in nowcasting has gained momentum in recent months. A premise that can be corroborated by looking at data from Google trends. According to the latter, between 26 April and 2 May 2020, the highest number of searches for the keyword "nowcastïn the last two years was reached. In this context, in 2020, there was a strong interest in the development of alternative and more challenging forms of nowcast forecasting tools that would substantially improve macroeconomic projections.

Among them we can highlight the work of (31) where they developed a mixed-frequency reconciliation model that produces monthly estimates of real GDP, including stochastic volatility extensions and error distributions that are broad-tailed or explicitly allow for outliers, correcting for extreme observations by Covid-19. They find in terms of NowCast densities, that many of the extensions lead to larger predictive variances that reflect the large uncertainty of the pandemic months. Also the work by (21) present a new dynamic factor approach using timely and correlated publication databases using economic and financial time series plus real-time variables such as (daily) social mobility and significant themes extracted by Google Trends during the pandemic.

Now, not only have there been improvements in forecasting economic activity, but also, in the employment NowCast, in (33) work, taking into account unprecedented shocks to employment, they explore the performance of models with different information sets and data structures in order to better project US initial jobless claims. They even develop a state-level panel model, which takes advantage of variation in the timing of state of emergency declarations, also performs better than models that include Google Trends. The results suggest that in times of structural change there is a trade-off between bias and variance. The striking point is that the findings support the view that simple autoregressive models miss dramatic changes, but show that in certain cases it is possible to exploit panel information if there is information about differences over time in the cross-section.

Another paper that marks a new departure for Nowcast models and would allow better use of corporate information is the work of (3), as they use a standard dynamic factor model to extract new factors based on the real-time flow of accounting data from corporate financial reports. They show that such weekly updated accounting factors are increasingly relevant for forecasting and predicting the main components of economic output in the National Accounts, pioneering the incorporation of the continuous flow of accounting data into the dynamic factor model.

Another striking case is a World Bank paper by (41), who developed a NowCast using Google's mobility indices for a set of countries. From the pandemic, Google reports mobility at the municipal level and with daily frequency, including various indicators such as trade, transport stations, workplaces, etc. that have shown strong relationships with economic activity. The work of (41) find a novel way to have a longer series of Google mobility. To increase the degrees of freedom in the analysis, the authors backcast the mobility data using daily weather and pollution data. The assumption is that pleasant weather and low pollution are correlated with increased mobility. This could be replicated for Antioquia, as the process is carried out in three steps:

1). Delayed mobility data are combined with air quality data;
2). The mobility data are combined to extract a common Mobility Index by Kalman;
3). A MIDAS approach predicts industrial production from the smoothed Mobility Index.

Finally, the work of Woloszko (2020) for the OECD of a NowCast from Google Trends. It is a two-step model for forecasting weekly GDP growth based on Google Trends. First, they estimate a quarterly GDP growth model based on Google Trends search intensities at a quarterly frequency. Second, the relationship between Google Trends and activity using the same elasticities to generate a weekly tracker.

The relationship between Google Trends variables and GDP growth is adjusted by a Machine Learning algorithm ("neural networks"). The 'BIG DATA' of Google trends (it can also be filtered for any country) makes it possible to use algorithms that are powerful, but require large samples.

The OECD algorithm extracts and compiles information on consumption (e.g. vehicle or appliance searches), vehicle and appliance searches, among others. labour markets (e.g. searches for unemployment benefits), housing (e.g. searches for real estate agencies or mortgages), business services (e.g. searches for 'venture capital or bankruptcy), industrial activity (e.g. searches for shipping or agricultural equipment), trade (e.g. searches for exports or freight), as well as economic sentiment (e.g. searches for recession) and poverty (e.g. searches for food banks). After statistical pre-processing, the selected variables are transformed into year-on-year growth rates, resulting in a weekly tracker.

Undoubtedly, alternative ways of estimating the current state of the economy have grown due to the impact of the pandemic and the rapid and timely response of governments. In this vein, this paper has as a distinctive novelty the combined use of Deep Learning and a two-stage estimation of the GDP Nowcast from Google Trends. That is, following the OECD approach, we collect Google Trends information on selected keywords with high dynamic correlations with the GDP of the corresponding country, in order to estimate a latent factor by means of a dynamic factor model (weekly and monthly). However, due to the disruptive changes caused by the pandemic, the prediction of this type of models is deficient, so here comes the different Deep Learning models. Given the increasing availability of data and computing power in recent years, Deep Learning has become a fundamental part of the new generation of Time Series Forecasting models, obtaining excellent results.

Although Machine Learning type models have been estimated, the use of Deep Learning for time series forecasting overcomes the traditional disadvantages of machine learning with many different approaches (LSTM, GRU, TCN, CNN, MLP). Deep learning neural networks can automatically learn arbitrary complex input-output mappings and support multiple inputs and outputs. Achieving a unique combination of factor models and Deep Learning for the Nowcast of advanced and emerging economies from Google Trends.

The remainder of this paper is divided as follows: It consists of a short section presenting the use of Deep Learning in macroeconomics, continues with a description of the dynamic factor nowcasting model for latent factor extraction from Google Trends keyword searches, then with the estimation and validation of the models using Python, and ends with a section of results of the different Deep Learning models for different economies. To show how well the model performs in terms of pattern identification and prediction, a range of DL models are presented with their error metrics (MAE) to identify the most accurate, consistent and fast model for use as a forecasting tool in advanced and emerging economies in post-pandemic times.

3. Deep Learning for Macroeconomics

Artificial intelligence is growing by leaps and bounds, largely due to the computational advances of the last decade, and it is increasingly difficult to isolate macroeconomic analysis from this reality. One of the recent works that is causing a turning point in macroeconomics is the publication by three economists on the implications of artificial intelligence entitled "Prediction Machines: The Simple Economics of Artificial Intelligence"by (4), where they analyse and develop the advantages of machines and computational development to correct biases (judgements) of economists, one of the fragments that can "synthesise"the object of the document and that has gained popularity has to do with the famous phrase "Machines do not make judgements, humans do"; Another interesting and highly popular paper that contributes to the debate on the backwardness of macroeconomics in using Artificial Intelligence tools to complement models is 'How is Machine Learning

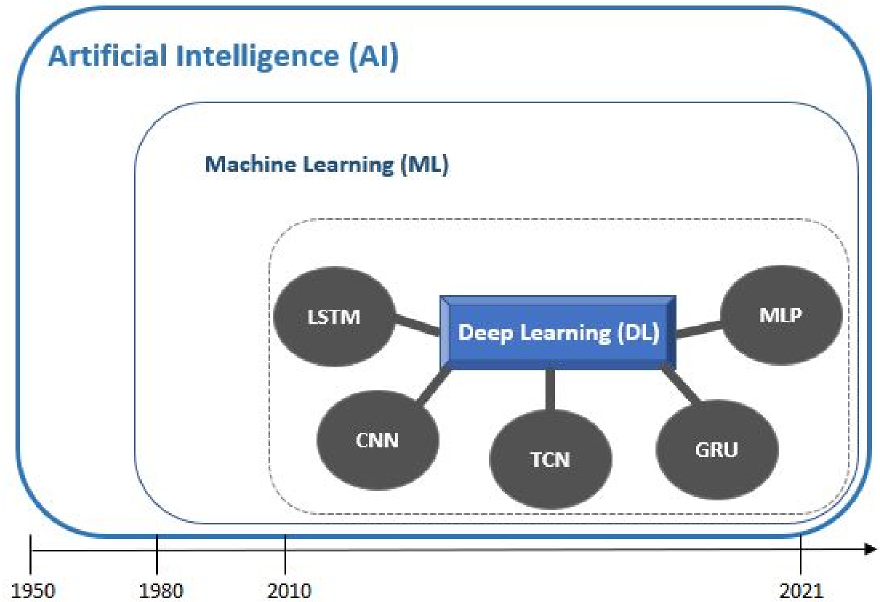
Useful for Macroeconomic Forecasting?' by (22), their thesis revolves around the criticism towards economists in forecasting macroeconomic variables and their insistence on sticking with traditional models, such as Dynamic Stochastic General Equilibrium (DSGE) and Vector Autoregressive (VAR) models that were not effective in predicting the 2008 financial crisis and cost them in times of Covid-19, mainly due to disruptive changes, but without ignoring the importance of the economist: 'As forecasting machines make forecasts better and better, faster and cheaper, the value of human judgement will increase because we will need more of it' (22).

In this sense, in the emerging literature, there is growing interest in integrating this type of techniques to significantly reduce prediction errors and lags in the publication of macro information, taking advantage of the high volumes of Big Data, in this line is putting all its efforts in the work of the International Monetary Fund (IMF) as (13) and (46).

Artificial Intelligence has evolved towards the topics of Machine Learning and Deep Learning during the last decade, being undoubtedly one of the most popular topics nowadays. In short, Machine Learning and Deep Learning are a set of mathematical and statistical methods that attempt to mimic human behaviour, especially because of the overriding characteristic "they learn". In the following, in figure 2, an overview of AI is presented, where a wide range of modelling possibilities in the DL field can be noticed, such as Long Short-Term (LSTM); multilayer neural networks (MLP); convolutional neural networks (CNN); temporal convolutional neurons (TCN); Gated Recurrent Unit (GRU).

Economic activity by its very nature has a high degree of complexity, mainly because it depends on the interaction of multiple agents that contribute to the formation of GDP in the country. Such behaviour causes forecasts to have a high level of uncertainty.

Figure 2: **Generalised outline of artificial intelligence techniques**



Source: Own elaboration with information from Paluszek and Thomas (39); Hastie et al. (29) and Pedregosa et al. (40).

Along these lines, forecasting is now based on a large number of machine learning techniques, which are covered theoretically and conceptually extensively in Hastie et al. (29) in the guidebook entitled "The elements of statistical learning: data mining, inference and prediction", and more recently for deep learning with the same level of detail in Goodfellow et al. (28) As far as programming is concerned, Python has a very complete library for machine learning called "Scikit-learn"which has multiple examples for each of the supervised and unsupervised models. Supervised learning will be the analytical focus of the paper.

3.1. Supervised learning

Supervised learning is understood as the existence of an external agent that knows the response that the network should generate from a given input, in simple terms, that the output obtained is close to the desired one. Three main classes are known in the literature, following Méndez (37): error correction learning, reinforcement learning and stochastic learning.

Within the broad set of models presented in Figure 2, one of the most popular are artificial neural networks, which emerge in macroeconomics on two fronts: parametric and non-parametric regression (prediction) and classification. The multilayer perceptron is one of the most widely used. The distinctive and original novelty of neural networks is learning, since they learn from the data, without the need to determine a structure for the system we wish to produce, or to place the probability distribution within a specific family (37). Their structure consists of a network made up of nodes (or neurons) and connections, which is why they resemble the human brain, from which they get their name (Moreno, 2010). Recurrent neural networks can be applied to a variety of problems, including, in our case, pattern recognition, which is fundamental in macroeconomic time series such as GDP, oil prices, inflation, the exchange rate and unemployment, among others, and, secondly, for function approximation, due to their flexibility and ease of use, which allows combining macroeconomic theory and making economic sense of the prediction, while respecting the evolution of the data in the economic reality. The learning of the network consists fundamentally of modifying the weights that connect the nodes (37).

Supervised recurrent neural network models allow the interaction or aggregation of variables either in the past time or having future information, the choice is made whether a model needs to be trained to make a prediction.

The fundamental importance of a neural network for macroeconomics consists in the ability to detect complex and non-linear relationships between time series, which both theoretically and in practice have some kind of relationship that is not necessarily linear, starting from very simple units such as neurons, since multiple layers can be created in parallel. The network is composed of input variables, which in our case are the time series of the latent factor for each of the periods from 2004 to the most recent publication (March 2021), all of which are collected on a monthly and/or weekly basis, their publication is easily accessible on Google Trends. Now, the output variables are related to the prediction of the economic activity of the corresponding country (month t, against the same month year t-1).

Deep neurons in macroeconomics can be constructed depending on the research objective in different layers. The operation of a neuron consists of transforming the values of the inputs through the connections into an output. The output is obtained from a propagation function, an activation function, and a transfer function.

The additional advantage in the field of macroeconomics of the use of neural networks is that it is not necessary to assume a functional form which limits the accuracy of forecasts as in AR, MA, ARIMA, ARIMAX, ARMA, ARDL, SARIMA, VAR models, and multicollinearity is not relevant because of the underlying feature of artificial neural networks to detect complex and non-linear relationships between macro time series.

After having defined the number of sufficient layers of input variables, we proceed to a fundamental phase and the heart of this type of models, the training of the network, in this phase is where we enter the world of Machine Learning and Deep Learning itself. Training is an iterative algorithm, therefore, it requires a starting point and a stopping rule. The use of the network relies on it being able to reproduce the underlying behaviour of the input data, which implies the minimisation of a cost or error function, i.e. that the output of the network approximates the output of the data. The most common cost function is the mean squared error (MAE), although RMSE, MSE and RMSLE are also calculated in the paper.

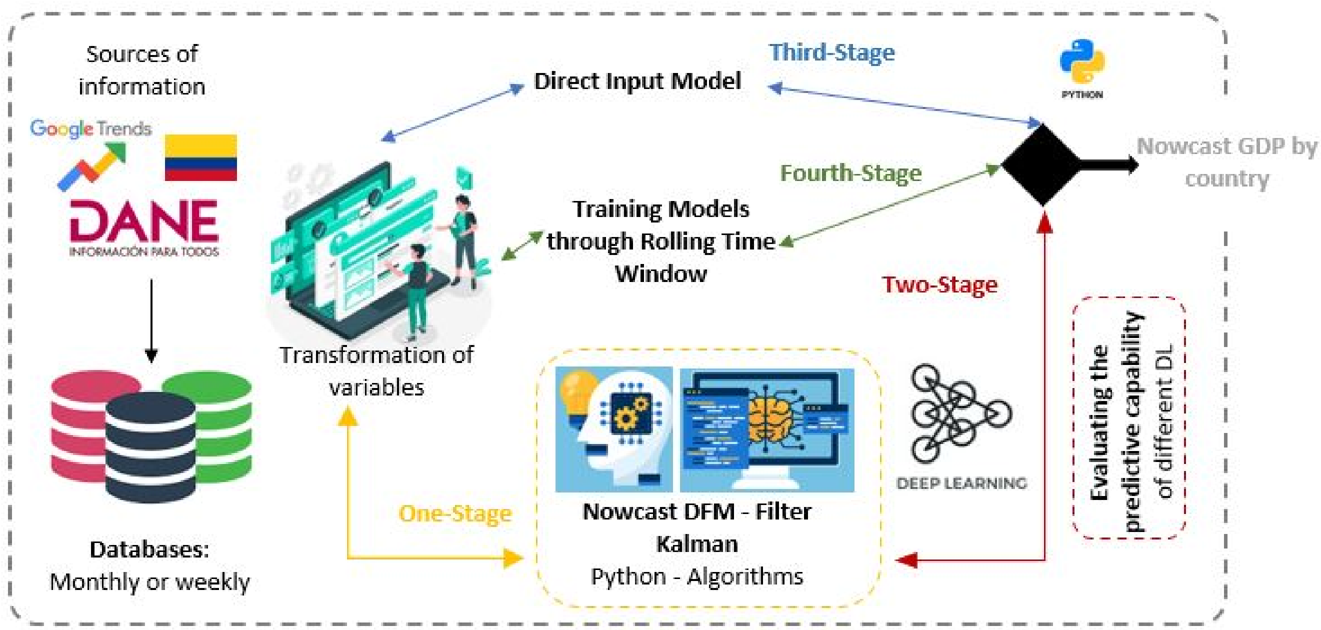
What nowcasting basically seeks to do is to take advantage of the periodic publication of Google Trends words by estimating an immediate monthly forecast that is equivalent to the real value of the country's quarterly

GDP, at least 40 days in advance, providing faster, more accurate and timely information for economic authorities.

4. Methodology: A new Fourth-stage Nowcasting in times of disruptive change.

Undoubtedly the best way to forecast the future is to create it, therefore, the nowcasting literature is interested in estimating existing economic indicators (typically quarterly GDP growth) in real time. In this paper Nowcasting will be understood as the set of high frequency (weekly and/or monthly) Google Trends keywords to forecast the country's quarterly GDP in a fast, accurate and timely manner. Taking into account the delay in the publication of the information of the main macro figures, it seeks to reflect in a timely manner the pace of the real economic activity of each country, the novelty in the model is that there will be a first phase that will use dynamic factor models to extract the latent factor, to estimate in a second stage multiple Deep Learning models that overcomes the traditional disadvantages of econometric models in disruptive times. Below is a schematic that summarises the construction process.

Figure 3: **Fourth-stage construction process of Nowcast-GT-DL**



Source: Own elaboration.

4.1. First Stage: Dynamic factorial model

We present the modelling of nowcasting in a general way, following the seminal work of (43); (26) for forecasting US quarterly GDP, and the notation of the work of (25) for nowcasting of Mexican GDP, in this way, it can be formally expressed. For the latter, we will first specify the notation: Y_t^Q :Monthly GDP growth in the country. This comes from a weighting of the words in Google Trends searches in their respective languages.

IM_t: Set of high frequency (weekly and/or monthly) Google Trends search keywords. From non-conventional sources, e.g. "Hotel", Çar", "Flights", Restaurant", among others.

Since we have multiple frequency data, it is necessary to make an additional notation, which differentiates the period we are working with. Where the superscript Q refers to monthly variables and the subscript t refers to time (day, weeks, months).

The aim is to estimate regional monthly economic activity in "pseudo real time", therefore, the linear projection of GDP is estimated given the set of information IM_t.

$$Proy\left[\frac{Y_t^Q}{IM_t^Q}\right]$$

For each economy, the information set is composed of n variables, $IM^Q_{it/cj}$, where $i = 1,\ldots,n$ identifies the individual time series from 2004 to the latest published data (March, 2021), and $t = 1, \ldots, T_{cj}$ denotes the time, which changes between series c_j.

Thus, our nowcasting is calculated as the expected value of GDP conditional on the available information and the underlying model, (in this case the factor dynamic model, see Figure 1), under which the conditional expectation is calculated:

$$Y^Q_t = E[Y^Q_t \hat{/} IM^Q_{c_j};\omega]$$

Because the number of observed data is increasing over time and with weekly and/or monthly updating, the error variance is decreasing, which means that the error variance is decreasing:

$$Var_{Y^Q_t/c_j} \leq Var_{Y^Q_t/c_{j-1}}$$

4.1.1. Dynamic factor modelling for each country from Google Trends

The general idea is that the observed (economic factors) depend on an unobserved state f (latent factor), where $theta_t$ and mu_t are errors that are assumed to be white noise. That is, a small number of unobserved "factorsçan be used to explain a substantial part of the variation and dynamics in a larger number of observed variables. In addition to producing estimates of unobserved factors, dynamic factor models have many uses in macroeconomic forecasting and surveillance (25).

Dynamic Factor Models (DFM) were first developed and applied by Giannone, Reichlin and Small (2008) to forecast quarterly US GDP. However, the original idea of using Spatial State Models (SSM) in order to obtain coincident US indicators had already been proposed and studied by Stock and Watson (1988, 1989), based on the original proposal by Geweke (1977). Following (9) and (25) the basic specification part of the typical "static form.ºf the dynamic factor model is given by the following state-space representation:

$$X_t = \nabla f_t + \xi_T, \xi \sim N\left(0, M_\xi\right) \tag{1}$$

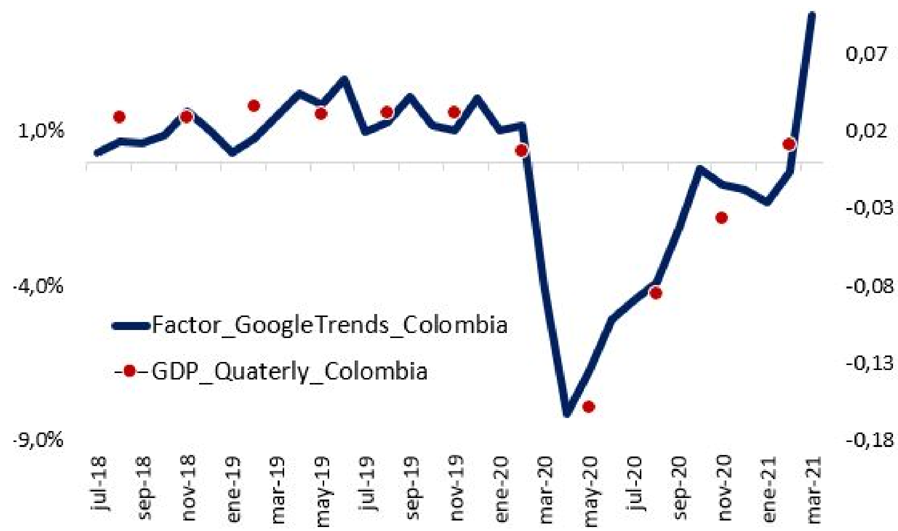
$$f_t = \sum_{i=1}^{p} A_i f_{t-i} + \theta_t \tag{2}$$

$$\theta_t = B\mu_t, \mu_t \sim N\left(0, I_q\right) \tag{3}$$

Being ∇ a matrix nxr of weights, which implies that E1 relates the monthly series X_t (in our case for example the Google Trends series) to a vector of latent rx1 $f_t = (f_{1,t},\ldots,f_{r,t})$plus an idiosyncratic component $\varepsilon_t = (\varepsilon_{1,t},...,\varepsilon_{n,t})\prime$. The latter is assumed to be white noise with a diagonal covariance matrix $M_varepsilon$. In our model, an autoregressive factor of order 4 is used, together with a process of order 4 in the errors, choosing the least Bayesian criteria AIC, BIC and HQIC.

Equation 2 describes the law of motion of the latent factors f_t which are driven by an autoregressive process of order p, plus a q-dimensional white noise, where B is a matrix xq, and where q is r. Implying the number of common shocks, q, is less than or equal to the number of common factors r.In this way, the latent (unobserved) factor of the series of words extracted from Google Trends is obtained for each of the countries.

Figure 4: **Latent factors from Google Trends**



Source: Own elaboration.

4.2. Second Stage: Deep Learning Models for Time Series

In the last decade, the field of neural networks has undergone several innovations that have led to what is known as Deep Learning. In particular, one of the traditional problems of neural networks had always been the large computational cost of training large models. However, that changed completely when he showed that a deep belief network could be trained efficiently using an algorithm called layered greedy pre-training. As related developments followed, researchers began to efficiently train complex neural networks whose depth was not limited to a single hidden layer (as in traditional MLP). As these new structures consistently showed better results and generalisation capabilities, the field was renamed deep learning (DL) to emphasise the importance of depth in the improvements achieved (32).

While this success of Deep Learning (DL) models started in computer applications, for example image recognition, speech recognition or machine translation, the benefits of DL have also been extended in recent years to various applications related to series time, especially in energy markets such as the works of Al Khafaf et al., (2019); Hrnjica et al., (2020); Bendaoud Farah (2020). Among these areas, it could be said that wind energy forecasting is possibly the field that has benefited the most, the work of Wang et al., (2016) shows how, using a network of deep beliefs and quantile regression, it can be improved the probabilistic forecast of wind speed. Similarly, other documents such as those by Coelho et al., (2017) propose a deep feature selection algorithm that, in combination with a multi-model framework, improves the accuracy of the wind speed forecast by 30 percent. In the same research area Hu et al., (2017) propose a set of convolutional neural networks (CNN) to obtain more precise wind energy probability forecasts.

Following the work of (32) shows that in addition to wind energy applications, DL has also proven to be successful in other related fields. In the literature, there are different types of DL models: Deep Multilayer Perceptron (DMLP), RNN, LSTM, CNN, Restricted Boltzmann Machines (RBM), DBN, Autoencoder (AE) and DRL (34). DL is a type of ANN that consists of multiple layers of processing and enables high-level abstraction for modeling data. Five approaches will be used in this document:

Recurrent neural networks (RNN), which are the most classical architecture and used for time series prediction problems. In fact, as in standard neural networks, neurons are divided into input layer, hidden layer, and output layer. Each connection between neurons has a corresponding trainable weight.

The difference is that in this case each neuron is assigned a fixed time interval. Neurons in the hidden layer are also forwarded in a time-dependent direction, which means that they are all fully connected only with neurons in the hidden layer with the same assigned time step, and are connected with a one-way connection to each neuron. assigned to the next time step.

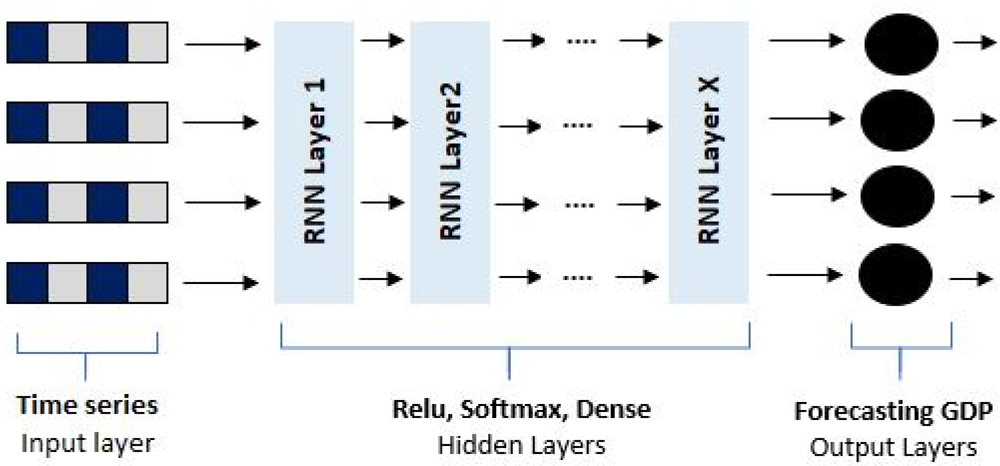
Since the output of the hidden layer of one time step is part of the input of the next time step, the firing of neurons is calculated in time order: at any given time step, only the neurons assigned to that step of time calculate their activation.

In general, RNNs solve many problems of traditional machine learning models for time series forecasting. The performance of the recorded neurons is not significantly affected by the missing values; RNNs can find complex patterns in the input time series; RNNs are good at forecasting more than a few steps; and RNNs can model the data sequence so that each sample can be assumed to depend on the previous ones. nonlinear relationships. The RNN model architecture consists of different numbers of layers and different types of units in each layer (42). The equation (4) y (5) ilustrate RNN formulations used. The equation (6) shows the total error, which is the sum of the error form each time iteration.

$$h_t = W f\left(h_{t-1}\right) + W^{hx} x_{[t]} \tag{4}$$

$$y_t = W^{(s)} \tag{5}$$

$$f\left(h_t\right) \frac{\partial E}{\partial W} = \sum_{t=1}^{T} \frac{\partial E_t}{\partial W} \tag{6}$$



Source: Own elaboration with information from Goodfellow et al. (28) and Hastie et al. (29).

On the other hand, there is the famous model of time series, Long Short-Term Memory (LSTM), which are an evolution of the NRNs developed to overcome the problem of the disappearance gradient. This is achieved by using an LSTM unit instead of the hidden layer.

LSTM is a type of RNN where the network can remember both short-term and long-term values. LSTM networks are the preferred choice of many DL model developers when tackling complex issues such as automatic speech and handwritten character recognition. LSTM models are primarily used with time series data. (14).

Following the (42) notation below is the architecture of the LSTM used. The following equations show the form of the implemented LSTM unit, where x is the input vector (time series); l is the activation of the forgetting gate; i is the activation vector of the input gate; s the activation vector of the output gate; h the output vector with the nowcast per country, z the cell state vector; sigma the sigmoid or Relu function depending on the country; and sigma h the hyperbolic tangent function; b the bias parameter; finally W and U the weight matrices which is where the network learns the latest disruptive changes caused by the pandemic.

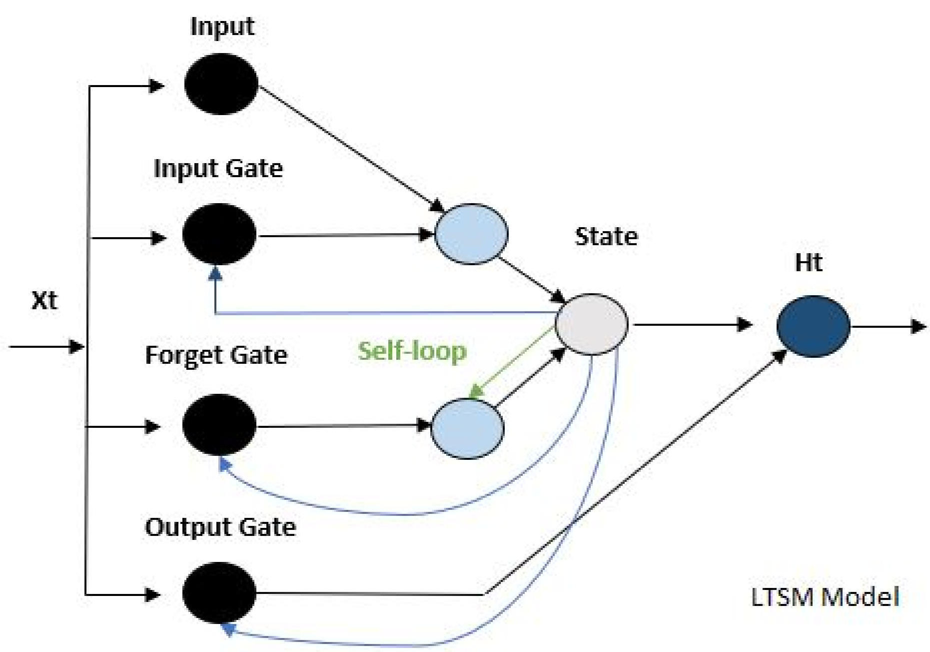
$$l_t = \sigma_g \left(W_l x_t + U_l h_{t-1} + b_l \right) \tag{7}$$

$$i_t = \sigma_g \left(W_i x_t + U_i h_{t-1} + b_i \right) \tag{8}$$

$$s_t = \sigma_g \left(W_s x_t + U_s h_{t-1} + b_s \right) \tag{9}$$

$$z_t = l_t * z_{t-1} + i_t * s_z \left(W_z x_t + U_z h_{t-1} + b_z \right) \tag{10}$$

$$h_t = s_t * \sigma_h \left(z_t \right) \tag{11}$$



Source: Own elaboration with information from Goodfellow et al. (28) and Hastie et al. (29).

Gated recurrent units (GRU) it is a new generation of recurrent neural networks and is very similar to an LSTM. To solve the disappearing gradient problem of a standard RNN, GRU uses the update gate and the reset gate. These are two doors that decide what information should be passed to the exit (Brownlee, 2018). These two gates can be trained to hold information many time steps before the real time step, without washing it over time, or to remove information that is irrelevant to the prediction. If trained carefully, GRU can perform extremely well even in complex scenarios.

Deep multilayer perceptrons (DMLP) their difference from shallow networks is that DMLP contains more layers. Generally, neural networks such as multilayer perceptrons or MLP provide capabilities that some algorithms offer, according to (14) such as: Robust to noise. Neural networks are resistant to noise in the input data and in the mapping function and can even support learning and prediction in the presence of missing values; Non-linear. Neural networks do not make strong assumptions about the mapping function and they easily learn linear and nonlinear relationships. The equation (12-17) ilustrates the output of neuron in the Neural Network (NN). The different non-linear activation functions used are presented.

$$y_i = \sigma\left(\sum_i W_i x_i + b_i\right) \tag{12}$$

$$\sigma(r) = \frac{1}{1+e^{-r}} \tag{13}$$

$$tanh(r) = \frac{e^r - e^{-r}}{e^r + e^{-r}} \tag{14}$$

$$R(r) = max(0,r) \tag{15}$$

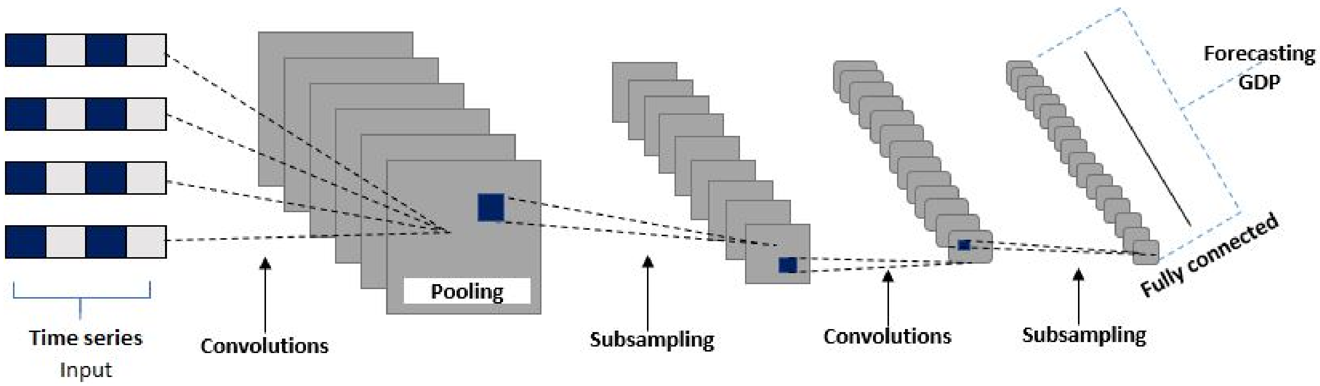
$$(r) = 1(x<0)(\alpha x) + 1(x>=0)(x) \tag{16}$$

$$softmax(r_i) = \frac{exp * r_i}{\sum_j exp * r_j} \tag{17}$$

The weights in our work are adjusted to measures that the epochs (iterations) are implemented by means of the ADAM optimizer. The latter is an updated version of RMSProp that uses running averages of both the gradients and the second moments of the gradients (42).

Convolutional Neural Networks (CNN) is a type of DNN that consists of convolutional layers based on the convolutional operation (Lecun et al, 2015). CNN are a type of neural network that was designed to handle image data efficiently. In CNN architectures, there are different layers: convolutional, maximum pooling, dropout, and fully connected multilayer perceptron (MLP) layer. (42). The ability of CNNs to automatically learn and extract characteristics from raw input data can be applied to time series prediction problems. A sequence of observations can be treated as a one-dimensional image that a CNN model can read and distill into the highlights. (14).

Figure 5: **CNN construction process of Nowcast GDP-GT-DL**



Source: Own elaboration with information from Goodfellow et al. (28) and Hastie et al. (29).

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)\, w(t-a) \tag{18}$$

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)\, K(i-m, j-n) \tag{19}$$

$$d_i = \sum_j W_{i,j} x_j + b_i \tag{20}$$

$$y = softmax(d) \tag{21}$$

$$softmax(d_i) = \frac{exp(d_i)}{\sum_i exp(d_j)} \tag{22}$$

CNNs get the benefits of multilayer perceptrons for time series forecasting, that is, support for multivariate input, multivariate output, and learning of arbitrary but complex functional relationships, but they do not require the model to learn directly from delay observations. Instead, the model can learn a representation of a large input sequence that is more relevant to the prediction problem.

4.3. Third Stage: Direct Input Model

As it is well known up to the moment, one of the key factors of DL is the well adaptation to non linearity, specially in macro-economical aspects (see for example (20) and (18)). Therefore, it is worth to evaluate whether a direct data input is appropriated for a DL structure. To include this approach, the time series for the several keywords were included directly after a re normalization. This is, ignoring the dynamic factor in order to treat each variable as a multivariate time series approach, that are well known.

The first method applied to the data was a noise reduction with the use of an auto encoder similar to the one proposed by (48). Given that the weekly data was used for the Google queries. But only monthly data is available for the target. Then, it is needed to perform an imputation of daily data for the desired output time series, or a monthly relabel of the data contained in the Google Trends. Both of the options were implemented, since both of them represent considerable benefits: The augmentation of the data sample, or the continuity of the data and avoiding the naive assumption development of the GDP. For both of them, the one found to work better was bagging repetitively the Google Trends data in order for it to match the value of the current GDP factor, this holds specially true when input data hadn't been smoothed previously. So, this was the method selected to continue this part of the analysis.

Two models were proposed for this segment, the direct implementation of a Deep LSTM network and a more robust one consisting of an auto-encoder previous to the LSTM network consisting of four layers and the bottle neck which was expected to identify and captures most important factors from the multivariate series. Nonetheless, the experiments shown that if resulted much useful to increase slightly the number of layers of the simple LTMS network in order to decrease loss. Both models in this phase were implemented using the PyTorch Lightning Framework (pt).

An additional tool was also used in order to improve the performance of the model: The assignation of a new variable which contains the last value of the Target. This is implicitly asking the model to be more aware of the last reported value. Also, in order to tune the hyper parameters of the model, a reinforced learning algorithm was used from the library (ray). Moreover, since the computational task was considerably high, the model was trained using a GPU instance.

4.4. Fourth Stage: Training Models through Rolling Time Window

Data regarding both Google Trends and the target variable for the model have shown to have a higher number of anomalies detected at the time specific period of the Post-Covid Pandemic. This analysis for anomalies in the data regarding each time-series was implemented using a One Class Support Vector Machine (one class SVM) model, which has been shown by several author as a good approach well suited for similar problems ((45)).

Therefore, based in the skewness of the extreme value through the available data period, it would be a problem to perform the training process and evaluation. Then we propose to perform a cross-validation like evaluation in order to both compare the trained models and batches training intervals. The approach makes sense since a statistical analysis on several parameters like seasonality and stationarity are far from evident, and therefore is necessary to develop an appropriated bagging approach. ((49)).

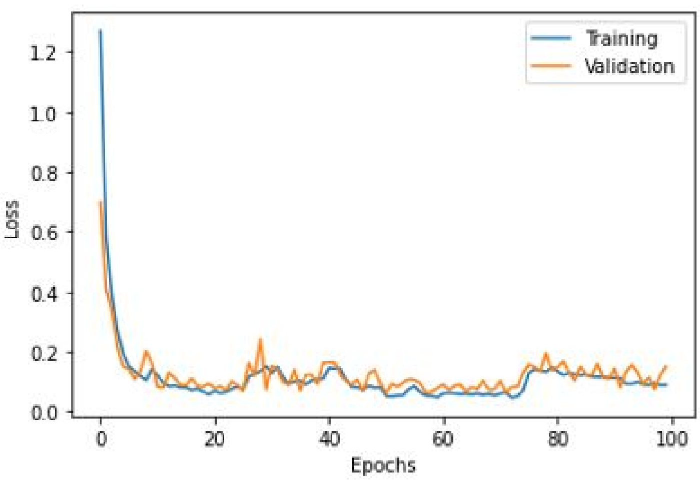
Essentially, the time series method consist of an evaluation of the entire data-set ordered in the natural way, in such a sense that the complete history can be reconstructed, as it is presented by (30). The reason why this is not likely to imply an over-fitting of the data is essentially that the generation of each batch implied a random sampling (clearly keeping the time order), in such a way the algorithm has never seen the real time-series, this type of approaches have been shown to lead to more robust models (11).

This cross validation can be useful, then to compare between all different algorithms and approaches, nevertheless shall not be the only one. the, the prediction horizon was kept at the end of the period, coinciding with the Covid-19 period.

5. Results

The results for the Colombia case study are presented below, from the estimation of a dynamic factor model in the first stage based on the Google words with the highest dynamic correlations with economic activity, then, this factor is predicted with different Deep Learning models explained in the previous section, and the MAE metric shown in Figure 6a is compared.

Figure 6a: **Nowcast-GT-DL model metrics**

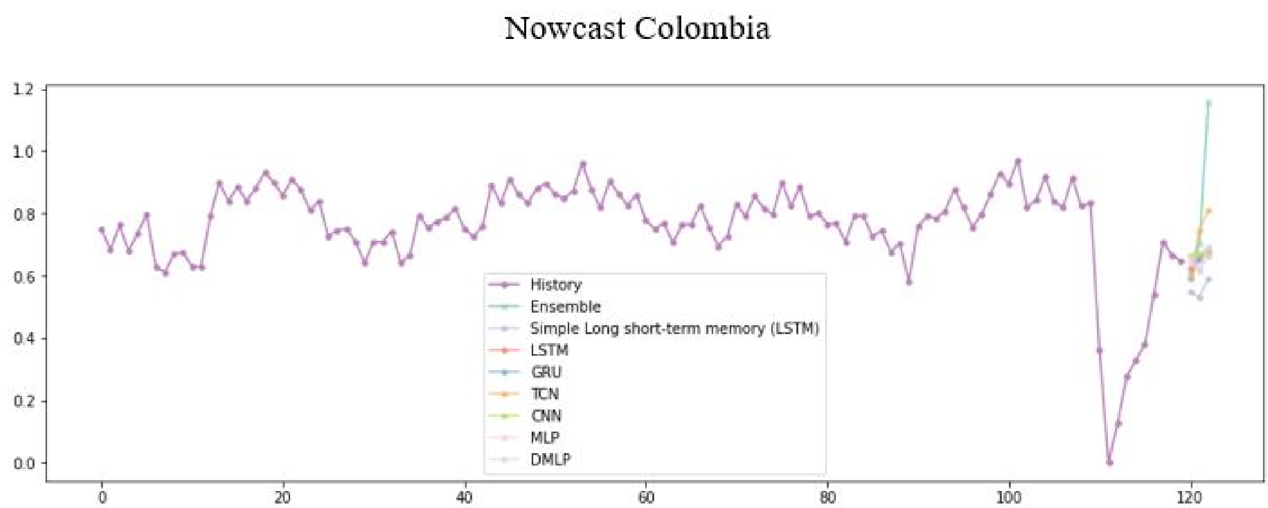



```
Simple Long short-term memory (LSTM)    0.045649
LSTM                                    0.046262
GRU                                     0.044287
TCN                                     0.150184
CNN                                     0.053221
MLP                                     0.045583
Name: MAE, dtype: float64
```

Source: Own estimation in Python (Tensor Flow).

Finally, figure 6b shows the estimation results of the combination of now casting models mentioned, where thepurple series are the data obtained from the Google Trends factor and the lines of the other colors show theimmediate prediction of the different models. Deep Learning. As evidenced, it is necessary to estimate differentranges of models.

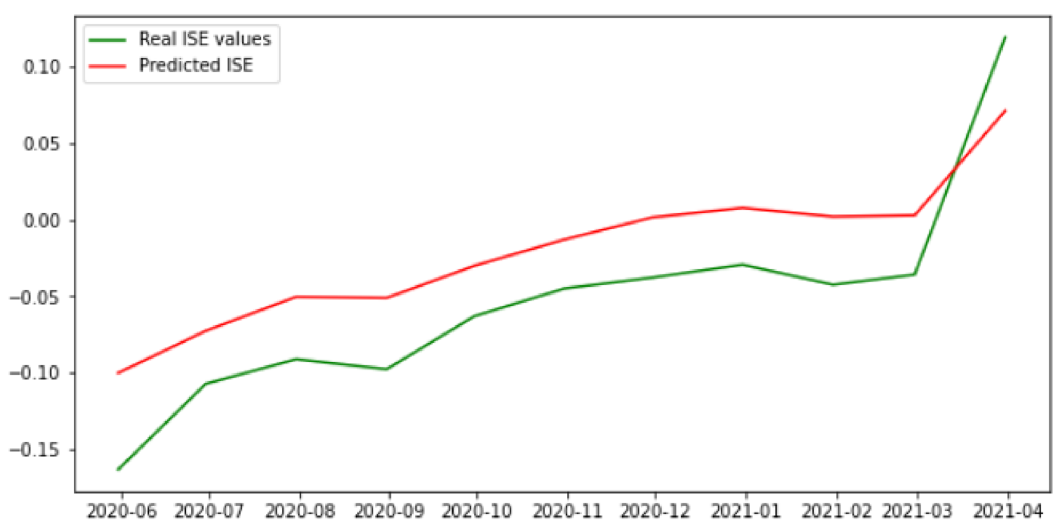
Figure 6b: **Nowcast-GT-DL results for Colombia with different model**



Source: Own estimation in Python (Tensor Flow).

We will now present the estimation results of stages 3 and 4. The test (prediction horizon) for the trained with direct results are shown in an example for Colombia's ISE in Figure 7a using the direct Input model.

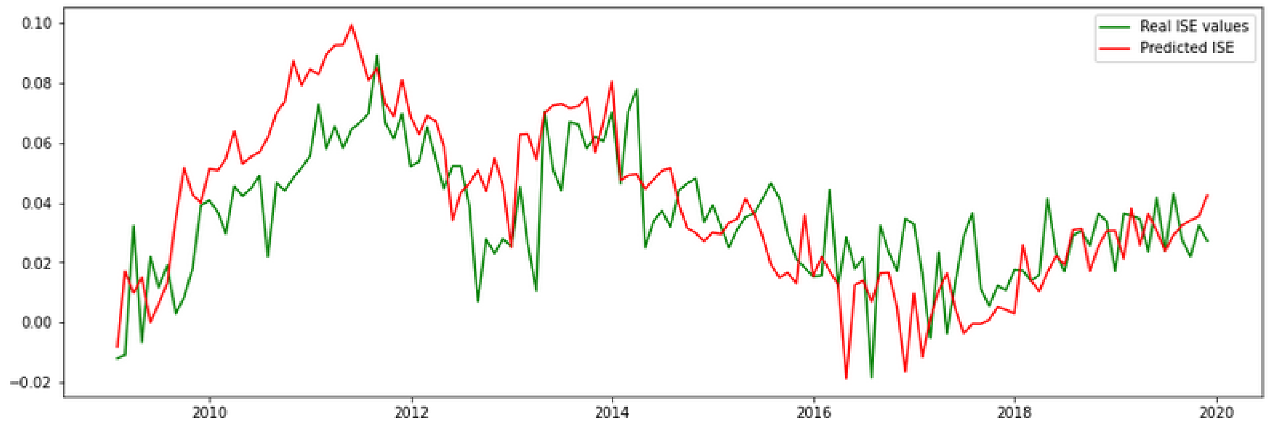
Figure 7a: **Colombia's prediction using the direct input LSTM with auto-encoder model**



Source: Own estimation in Python (PyTorch).

Also, the rolling window shows a good performance with the LSTM models, the Figure 7b shows how it fits throughout all the ISE's history:

Figure 7b: **Rolling validation for LSTM model in Colombia economy**



Source: Own estimation in Python (PyTorch).

Several approaches were considered in order to evaluate how the model would Learn from the data. One of the most popular ones being the Mean Absolute Error (MAE) and the Mean Squared Error (MSE). For both metrics, the direct LSTM model shows a better performance than the dynamic factor approaches, with a testing score of $MAE = 0{,}0089$ and a $MSE = 0{,}0018$.

6. Conclusions

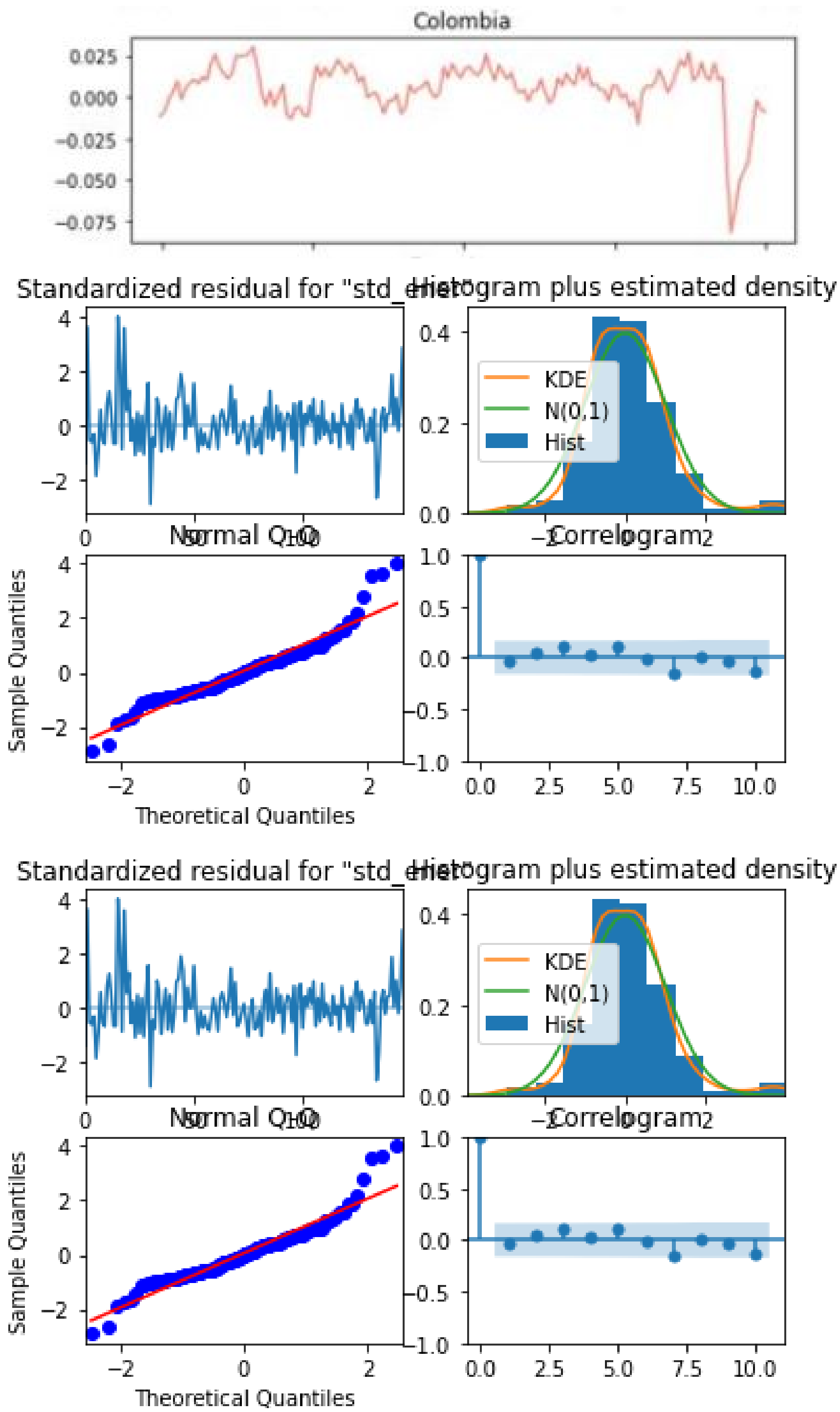
The integration of nowcasting DFM and Deep Learning, added to the appropriate selection of the main Google Trends keywords by country with the highest dynamic and significant correlations with respect to GDP, together form a diagnostic model of economic activity in "pseudo real time”. for its easy updating of Google Trends, being a fast tool, with a high level of precision and easy application by economic agents, eliminating the information gaps that occur in the dissemination of macro data in the advanced and emerging economies.

In the nowcasting models under the Deep Learning approach, a quarterly GDP projection was found that significantly improves due to the inclusion and increase of the information set and the use of deep neural networks for each factor due to its distinctive novelty, “learning”, which together they provide more accurate, faster and more timely estimates of GDP, without substantially increasing the revision error. And it has shown to be a future research area for the query for better algorithms and the most suited input variables. Suggesting that Deep Learning techniques from Google Trends could be an important part of the macro forecast toolkit of many countries in post-pandemic times.

Deep learning architectures have shown to be a good approximation for the description and analysis of economical data such as Colombias ISE. And as future outlook it is remarkably important to continue the serch for better algorithms, since here we shown that some of them are best suited for this kind of analysis.

7. Annexes 1

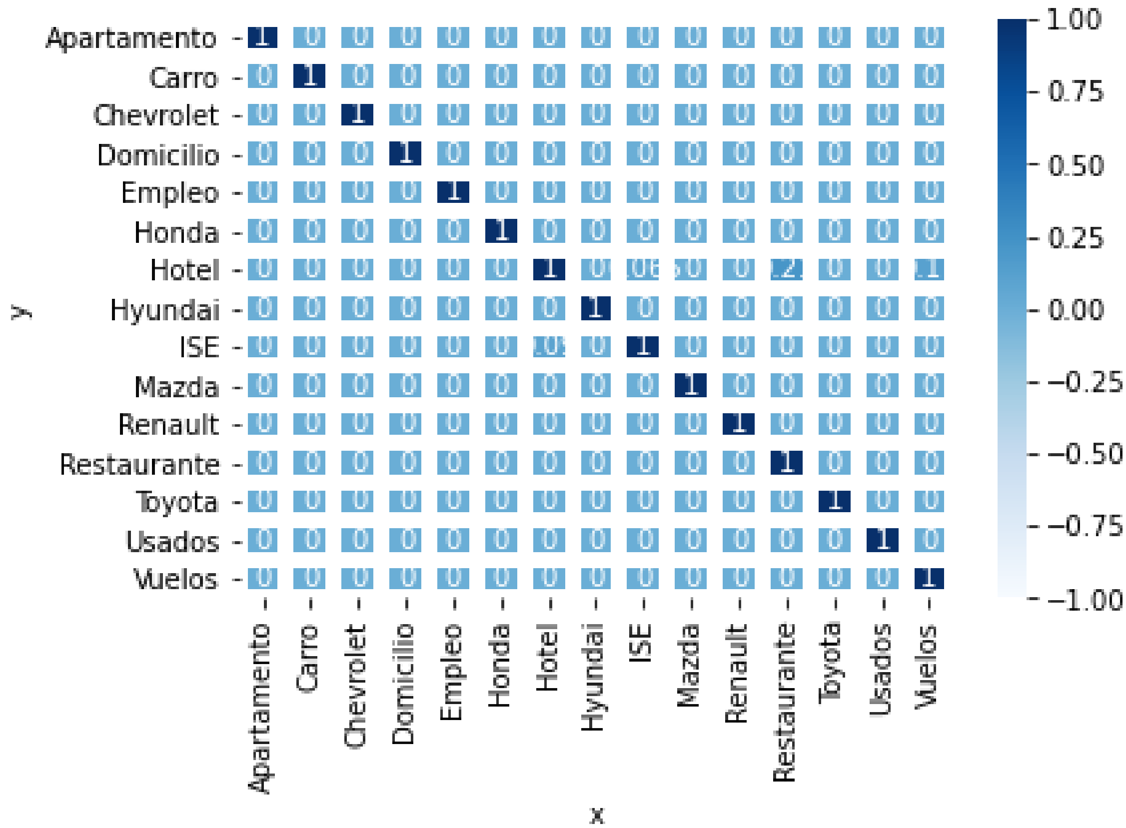
Figure 8a: **Factor extracted from searches in Google Trends for Colombia**



Source: Own estimation in Python (DFM) from Google Trends.

8. Annexes 2

Figure 8b: **Correlations activity economic with Google Trends for Colombia**



Source: Own estimation in Python from Google Trends Colombia.

Referencias

[pt] Pytoch lightning. `https://pytorch.org/ignite/`.

[ray] Ray rl. https://docs.ray.io/en/master/index.html.

[3] Abdalla, A. M., Carabias, J. M., and Patatoukas, P. N. (2021). The real-time macro content of corporate financial reports: A dynamic factor model approach. *Journal of Monetary Economics*.

[4] Agrawal, A., Gans, J., and Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

[5] Alvarado, E. D. Y. (2019). Un indicador de factores dinámicos para la evolución del pib a corto plazo para el ecuador. *Cuestiones Económicas*, 29(1):Emanuel–Daniel.

[6] Artola, C. and Martínez-Galán, E. (2012). Tracking the future on the web: construction of leading indicators using internet searches. *Banco de Espana Occasional Paper*, (1203).

[7] Askitas, N. and Zimmermann, K. F. (2009). Google econometrics and unemployment forecasting.

[8] Askitas, N. and Zimmermann, K. F. (2015). The internet as a data source for advancement in social sciences. *International Journal of Manpower*.

[9] Bańbura, M., Giannone, D., Modugno, M., and Reichlin, L. (2013). Now-casting and the real-time data flow. In *Handbook of economic forecasting*, volume 2, pages 195–237. Elsevier.

[10] Barhoumi, K., Choi, S. M., Iyer, T., Li, J., Ouattara, F., Tiffin, A., and Yao, J. (2020). A machine-learning approach to nowcast the gdp in sub-saharan africa.

[11] Bergmeir, C. and Benítez, J. M. (2012). On the use of cross-validation for time series predictor evaluation. *Information Sciences*, 191:192–213. Data Mining for Software Trustworthiness.

[12] Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., and Tambalotti, A. (2018). Macroeconomic nowcasting and forecasting with big data. *Annual Review of Economics*, 10:615–643.

[13] Bolhuis, M. and Rayner, B. (2020). Deus ex machina? a framework for macro forecasting with machine learning.

[14] Brownlee, J. (2018). *Deep learning for time series forecasting: predict the future with MLPs, CNNs and LSTMs in Python*. Machine Learning Mastery.

[15] Casares, F. F. (2017). Nowcasting: modelos de factores dinámicos y ecuaciones puente para la proyección del pib del ecuador. *COMPENDIUM: Cuadernos de Economía y Administración*, 4(8):25–46.

[16] Cepni, O., Güney, I. E., and Swanson, N. R. (2019). Nowcasting and forecasting gdp in emerging markets using global financial and macroeconomic diffusion indexes. *International Journal of Forecasting*, 35(2):555–572.

[17] Choi, H. and Varian, H. (2012). Predicting the present with google trends. *Economic record*, 88:2–9.

[18] Chong, E., Han, C., and Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications*, 83:187–205.

[19] Coble, D. and Pincheira, P. M. (2017). Now-casting building permits with google trends. *Available at SSRN 2910165*.

[20] Cook, T. and Smalter Hall, A. (2017). Macroeconomic indicator forecasting with deep neural networks. Research Working Paper RWP 17-11, Federal Reserve Bank of Kansas City.

[21] Corona, F., González-Farías, G., and López-Pérez, J. (2021). A nowcasting approach to generate timely estimates of mexican economic activity: An application to the period of covid-19. *arXiv preprint arXiv:2101.10383*.

[22] Coulombe, P. G., Leroux, M., Stevanovic, D., and Surprenant, S. (2020). How is machine learning useful for macroeconomic forecasting? *arXiv preprint arXiv:2008.12477*.

[23] D'Amato, L., Garegnani, L., and Blanco, E. (2015). Nowcasting de pib: evaluando las condiciones cíclicas de la economía argentina. Technical report, Working Paper.

[24] Fornaro, P. and Luomaranta, H. (2020). Nowcasting finnish real economic activity: a machine learning approach. *Empirical Economics*, 58(1):55–71.

[25] Gálvez-Soriano, O. d. J. (2018). Nowcasting del pib de méxico usando modelos de factores y ecuaciones puente. Technical report, Working Papers.

[26] Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4):665–676.

[27] González-Astudillo, M. and Baquero, D. (2019). A nowcasting model for ecuador: Implementing a time-varying mean output growth. *Economic Modelling*, 82:250–263.

[28] Goodfellow, I., Bengio, Y., Courville, A., and Bengio, Y. (2016). *Deep learning*, volume 1. MIT press Cambridge.

[29] Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media.

[30] Inoue, A., Jin, L., and Rossi, B. (2017). Rolling window selection for out-of-sample forecasting with time-varying parameters. *Journal of Econometrics*, 196(1):55–67.

[31] Koop, G., McIntyre, S. G., Mitchell, J., and Poon, A. (2021). Nowcasting 'true'monthly us gdp during the pandemic.

[32] Lago, J., De Ridder, F., and De Schutter, B. (2018). Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. *Applied Energy*, 221:386–405.

[33] Larson, W. D. and Sinclair, T. M. (2021). Nowcasting unemployment insurance claims in the time of covid-19. *International Journal of Forecasting*.

[34] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

[35] León, C. and Ortega, F. (2018). Nowcasting economic activity with electronic payments data: A predictive modeling approach. *Revista de economía del Rosario*, 21(2):381–407.

[36] Liu, P., Matheson, T., and Romeu, R. (2012). Real-time forecasts of economic activity for latin american economies. *Economic Modelling*, 29(4):1090–1098.

[37] Méndez, M. C. (2009). Modelización estadística con redes neuronales. aplicaciones a la hidrología, aerobiología y modelización de procesos. *Universidade Da Coruña*.

[38] Nagao, S., Takeda, F., and Tanaka, R. (2019). Nowcasting of the us unemployment rate using google trends. *Finance Research Letters*, 30:103–109.

[39] Paluszek, M. and Thomas, S. (2016). *MATLAB machine learning*. Apress.

[40] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al. (2011). Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830.

[41] Sampi Bravo, J. R. E. and Jooste, C. (2020). Nowcasting economic activity in times of covid-19: An approximation from the google community mobility report. *World Bank Policy Research Working Paper*, (9247).

[42] Sezer, O. B., Gudelek, M. U., and Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*, 90:106181.

[43] Stock, J. H. and Watson, M. W. (2006). Forecasting with many predictors. *Handbook of economic forecasting*, 1:515–554.

[44] Stock, J. H. and Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics*, volume 2, pages 415–525. Elsevier.

[45] Tian, Y., Mirzabagheri, M., Bamakan, S. M. H., Wang, H., and Qu, Q. (2018). Ramp loss one-class support vector machine; a robust and effective approach to anomaly detection problems. *Neurocomputing*, 310:223–235.

[46] Tiffin, A. (2016). Seeing in the dark: a machine-learning approach to nowcasting in lebanon.

[47] Yu, H., Szu, H. H., and Huang, H. (2019). Smartphones, grounds, satellites, uavs for earthquake nowcast. In *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, pages 0361–0365. IEEE.

[48] Zhao, X., Han, X., Su, W., and Yan, Z. (2019). Time series prediction method based on convolutional autoencoder and lstm. In *2019 Chinese Automation Congress (CAC)*, pages 5790–5793.

[49] Zivot, E. and Wang, J. (2003). *Rolling Analysis of Time Series*, pages 299–346. Springer New York, New York, NY.