PERUVIAN ECONOMIC ASSOCIATION

GDP nowcasting with Machine Learning and Unstructured Data to Peru

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Abstract

In a context of ongoing change, “nowcasting” models based on Machine Learning (ML) algorithms deliver a noteworthy advantage for decision-making in both the public and private sectors due to its flexibility and ability to drive large amounts of data. This document presents projection models for the monthly GDP rate growth of Peru, which incorporate structured macroeconomic indicators with high-frequency unstructured sentiment variables. The window sampling comes from January 2007 to May 2023, including a total of 91 variables. By assessing six ML algorithms, the best predictors for each model were identified. The results reveal the high capacity of each ML model with unstructured data to provide more accurate and anticipated predictions than traditional time series models, where the outstanding models were Gradient Boosting Machine, LASSO, and Elastic Net, which achieved a prediction error reduction of 20% to 25% compared to the AR and Dynamic Factor Models (DFM) models. These results could be influenced by the analysis period, which includes crisis events featured by high uncertainty, where ML models with unstructured data improve significance.

Clasification JEL: C32, C53, E37, C52, E32.
Key Words: nowcasting, machine learning, GDP growth.

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1 Introduction

Making decisions in real-time is a true challenge for policymakers, given that the primary barrier they face is the usual delay in the availability of updated information about macroeconomic aggregates. In most cases, the economic variables show a delay of between 30-45 days on average, including the time for revisions and retrospectives. Nevertheless, the continuous stride forward in the new generation of high-frequency data has changed how prediction models face the uncertainty inherent in this information. As a result, in the past few years, both central banks and international institutions have adopted methodological focuses that incorporate machine learning, and take advantage of the abundant quantity of data that come from search engines and social media (Richardson and Mulder, 2018).

These automated learning techniques have gained great popularity in comparison with the conventional focus of traditional models of temporal series that project macroeconomic variables. A characteristic of these algorithms that is often highlighted resides in their capacity to formulate parametric selections in big data sets, which find their base in training a specific percentage of the model's information. Hence, the objective of this document consists of exploring the benefits of utilizing diverse machine learning methodologies. This will be done by combining the use of conventional leading indicators (structured data) and indicators of analysis of sentiment (non-structured data) to build a precise monthly indicator of Peru's real GDP (Gross Domestic Product) growth. The data set consists of both local and international variables, which can be broken down into 53 structured variables in 38 nonstructured variables, giving a total of 91 predictors. These predictive variables are examined according to the model, to evaluate the optimum performance of each variable between September 2014 and May 2023. Further, following C. Romer and D. Romer (2008), an analysis of the evaluation of predictive adjustment will be carried out using two models as reference: the traditional autoregressive time series, and a dynamic factor model, based on the advanced indicator of widening electricity utilized by the economic literature, who are authorities in the political and economic consulting realm. This will facilitate an exhaustive evaluation of the performance of machine learning algorithms.

The results indicate that immediate predictions of the machine learning models are more solid in comparison with the benchmark auto-regressive model. Specifically, the Random Forest, Gradient Boosting Machine, and Adaptive Lasso show performance with a superior ability to reduce the average error of projection in a range from 20%-25%. Additionally, it is corroborated that following the methodology proposed by Armstrong (2001), the utilization of the average value of projection of all the machine learning algorithms, adds a significant value to the RMSE, which positively contributes to a more precise prediction of GDP. Even though other methodologies, such as *Ridge*, *LASSO* and *Elastic Net* do not reach the same level of predictive ability as the previously mentioned methodologies, they still outperform the control model in terms of performance. Further, the proof of predicting evaluation and exercises of consistency, confirm that most of the machine learning models improve the prediction significantly which falls in line with previous literature applied in other contexts (Richardson and Mulder, 2018; H. Varian, 2014; Q. Zhang, Ni, and Xu, 2023).

This research document adds itself to the existing literature that highlights the success of machine learning applications in contrast to more traditional methodologies. However, given the lack of evidence in Latin America, and in particular in Peru, surrounding the utilization of these algorithms in conjunction with non-structured data, this research project also highlights the need to bring to the forefront of the discussion what these models entail. Barrios et al. (2021), Richardson and Mulder (2018) y Döpke, Fritsche, and Pierdzioch (2017) have shown through the implementation of diverse machine learning algorithms that these method's results are more adequate in carrying out forecasts in real-time when a large amount of information is at the researchers' disposal. For example, Longo, Riccaboni, and Rungi (2022) carried out a forecast of trimestral GDP in the US for the combination of a neuronal recurrent network, and a dynamic factor model with a temporal variation of the median. This combination of models has demonstrated a substantial decrease in the forecast error, also showing a notable capability of capturing the period of recession caused by the COVID-19 pandemic and the economic recuperation that came thereafter. Similarly, in the case of El Salvador and Belize, Barrios et al. (2021) implemented a large array of machine, learning methods to forecast the trimestral growth of GDP, using a large amount of predictive variables. The results of this research study concluded that the application of these tools represents a solid alternative to prediction, and its benefits suggest a recommendation for its use in other countries in the region. Additionally, other researchers have extended the application of the machine, learning models further from GDP, including forecasting, inflation, yield curve, and active prices. These efforts have yielded notable results in precise forecasting (Medeiros et al., 2021; Giglio, Kelly, and Xiu, 2022).

It is still important to highlight that these methods present challenges in their implementation, which have led to some major debates surrounding the topic. De hecho, Green and S. Armstrong (2015), as well as Makridakis, Spiliotis, and Assimakopoulos (2018), when comparing multiple models of machine learning, find that the deposition of the forecasting is less significant in comparison with the statistical smoothing approaches, and the ARIMA models. These authors warn that the computational complexity that is inherent to the selection and use of variables in the machine learning model makes immediate forecasting difficult and less practical for policymakers.

Finally, the rest of this document is structured in several sections. Initially, a literature review is carried out that explores the relevance of the nowcasting methodology in the context of machine learning and big data, both at the national and international levels. After this, a section dedicated to the methodology is presented in which details are given about the models that were utilized and the data sets. Afterwards, the results are displayed in a specific section, followed by the robustness tests and the conclusion.

2 Literature review

Economists aim to provide the most accurate GDP forecasts using the most efficient approaches. Stock and Watson (1989), was the first to propose economic cycle indices using factor models. However, a critical challenge is the increase in uncertainty in the estimates, where traditional models, which use a limited set of variables, often fall short. The literature has been implementing new models with machine learning techniques that can address the trade-off between bias and variance.

To address the issue of extended delays in the publication of key economic aggregates, the concept of nowcasting is proposed, which aims to predict the present, the very near future and the very recent past (Bańbura, Giannone, et al., 2013). A traditional reference nowcasting model is the Dynamic Factor Model, widely used in central banks to predict GDP (Giannone, Reichlin, and Small, 2008; Bańbura and Rünstler, 2011; Bok et al., 2018). Two seminal articles have formalized this process into statistical models. On one side, Giannone, Reichlin, and Small (2008) proposed a methodology to assess the marginal impact of the publication of monthly-updated data on forecasts of quarterly-published real Gross Domestic Product (GDP) growth. The method presented by these authors was able to track the real-time flow of information that central banks monitor by handling large datasets with staggered publication dates. The proposed method works by updating primary forecasts (forecasts for the current quarter) each time new higher-frequency data is published. This is done using progressively larger datasets that reflect the unsynchronized data publication dates. On the other hand, Evans (2005) do real-time estimations of the current state of the US economy. This approach included data complexity and provided useful information about the relationship between macroeconomics and asset prices. This author models monthly time series with a dynamic factor model (Dynamic Factor Model - DFM) in a state space system. Once the state space representation is settled, Kalman filter techniques are estimated to make GDP forecasting, as they automatically adapt to changes according to the data available. We use a bounded DFM specification as a reference following Evans (2005) and the implementation suggestions of Doz, Giannone, and Reichlin (2012).

An additional bright side of the nowcasting models is the constant improvement experienced from wider information availability. Thus recently, machine learning methods are been incorporated enhances to the nowcasting approach. The algorithms of machine learning (ML) deliver better performance in handling large amounts of data, capturing non-linear relationships and adapting to changing economic conditions.

Those methods provide more accurate predictions by incorporating various variables and sources of unstructured data. As described Athey (2018), these techniques are divided into two main brands, supervised and unsupervised ML. Athey (2018) explains that unsupervised MLs are looking for groups of observations that are similar in terms of their covariance. Thus, a ”dimensionality reduction” can be performed. Unsupervised MLs commonly use videos, images, and text as a source of information, in techniques such as grouping *k-medias*. For instance, Blei, Ng, and Jordan (2003) applied pooling models to find ”topics” in textual data. Likewise, Athey and Markus (2017) assess the impact of the news type in *Google News* on Spanish consumer's decisions. Another example is the paper written by Woloszko (2020). Here, the author shows a weekly indicator of the economic activity for 46 OCDE countries and the G20 using search data from Google Trends. This document showcases the power of prediction of specific ”topics”, including ”bankruptcies”, ”economic crises”, ”investment”, ”baggage” and ”mortgages”. Calibration is performed using a neural network that captures nonlinear patterns, which are shown to be consistent with economic intuition using ML Shapley values interpretation tools. On the other side, the supervised ML algorithms as it is pointed out by H. Varian (2014) they imply the use of a group of variables features o co variables to predict an specific indicator result. There is a variety of supervised ML methods regressions such as *LASSO*, *Ridge*, *Elastic Net*,*Random Forest*, *Regression Trees*, *Support Vector Machines*, *Neural Nets*, *Matrix Factorization*, among others as *Model Averaging*.

Several studies highlight the advantages of supervised ML models to forecast macroeconomic series that overcome the traditional methods. An application is the research of Ghosh and Ranjan (2023), who present an compilation of Machine Learning techniques and conventional time series methods to predict the Indian GDP. They estimate the ML in DFM context with financial and economic uncertainty data. They estimate machine learning models such as Random Forest and Prophet along with conventional time series models such as ARIMA to nowcast Indian GDP, where hybrid models stand out. Likewise, the results from Richardson and Mulder (2018) shown better performance of the Ridge regression model to the nowcast GDP of New Zealand over a Dynamic Factor Model. Muchisha et al. (2021) built and compare ML models to forecast GDP of Indonesia. They evaluate six ML algorithms: Random Forest, LASSO, Ridge, Elastic Net, Neural Networks and Support Vector Machines. They use 18 variable between 3Q2013 y 4Q2019. Their results make clear the outstanding performance of ML than auto regressive models, especially the Random Forest model. Also, Q. Zhang, Ni, and Xu (2023) test ML, DFM and static factor and MIDAS regressions models to nowcast the GDP rate growth of China. They find superior accuracy of ML compare to DFM. The ML model who deserve more attentions was Ridge Regression, that overcome the others not only on prediction, but early anticipation to crisis such as global financial crisis and Covid-19. Kant, Pick, and Winter (2022) compare models to the Netherlands economy between 1992 and 2018, where Random Forest algorithms stood out. Suphaphiphat, Wang, and H. Zhang (2022) use novel variables such as Google Search and air quality. They run standard DFM and ML to European economies during normal times and crisis. They show that most MLs significantly outperform the AR(1) reference model. They highlight that DFM tend to perform better in normal times, while many of the ML methods have excellent performance in identifying turning points. Moreover, ML is able to predict adequately in very disparate economies. Moreover, Barrios et al. (2021) assess adjusted machine learning models to Belize and El Salvador economies where ML delivers good predictions, proving the effectiveness of ML algorithms in very different country context.

Other relevant aspect is the Big Data due to its benefits of broadening the range and use of available data that can provide some valid information on the behavior of the economy to anticipate certain economic indicators (Einav and Levin, 2014). As its mentioned in Eberendu et al. (2016), the digital era have allowed the emerge of news channels and social network technologies, mobile phones and online advertising. Nevertheless, the source of new type of data without pre fixed format arise new challenges. In fact, these data is available in formats like text, XML, email, images, videos, etc. In that sense, we can denominate these data such as no structured. Eberendu et al. (2016) gives and general description of this type of data. Some studies show relevant results on the use of these techniques. For instance, H. Varian (2014) indicate how the search related to the “initial claims for unemployment” in Google Trends are good candidates to forecast unemployment, CPI and consumer confidence in countries such as the US, UK, Canada, Germany and Japan. They focus on immediate out-of-sample forecasting and extend the Bayesian structural time series model using the Hamiltonian sampler for variable selection. These authors obtain good results for unemployment, while for CPI or consumer confidence not so good.

On the other hand, previous works applied to Peruvian economy are focused on the anticipated estimation of monthly GDP growth based on a set of leading indicators (structured data). However, a scarce application of machine learning models and the inclusion of unstructured data in GDP forecasting is evident. In particular, Escobal D'Angelo and Torres (2002) built a joint leading indicator that allows the track of Peruvian GDP with only 14 variables. On the other hand, Kapsoli Salinas and Bencich Aguilar (2002) perform forward GDP estimation with a nonlinear neural network model. Additionally, Etter, Graff, et al. (2011) propose a leading indicator with the expectations survey conducted by the Central Bank of Peru (BCRP). Also, Martınez and Quineche (2014) estimate the growth rate of GDP based on data of the electric production. Following to Aruoba, Diebold, and Scotti (2009), Forero, Aguilar, and Vargas (2016) propose a leading indicator of Peruvian economic activity. This indicator is obtained as an common unobservable component that explains the co-movement among six variables: electricity production, domestic cement consumption, adjusted domestic IGV, chicken sales, mining metal production and real GDP. Finally, Pérez Forero (2018) try to solve the difficulties about best leading indicators selection under the approach of H. Varian (2014). Forero estimate a stade state system trough the Bayesian Gibbs-Sampling methods and the spike-and-slab to the stochastic selection variables (SSVS) and calculated the probability of the inclusion of a large set of variables in the best model to predict GDP.

3 Methodology

This section provides a brief description of the different regularization methods and decision trees used to select the best predictors for the monthly nowcasting model and to calibrate the hyperparameters, in a series from January 2007 to May 2023. The six methods that are used are Random Forest (RF), Gradient Boosting Machine (GBM), LASSO regression, Ridge, Elastic Net, and as a benchmark, an autoregressive (AR) and dynamic factor model (DFM) are utilized.

3.1 Autoregressive Model (AR)

As a starting point for our reference, we establish an autoregressive AR model for the monthly GDP growth (y_t), which reflects the value of a variable in terms of its own previous values. A model of order 1, following these characteristics, exhibits the following structure:

$$y_t = \beta_0 + \beta_1 y_{t-1} + e_t \tag{1}$$

where β_0 is a constant term, β_1 is a parameter, and e_t is a term that represents the error and captures the randomness of the model.

3.2 Dynamic Factor Model (DFM)

DFMs are estimated in the form of state-space systems and can be estimated using the Kalman filter and various types of algorithms. The most popular in the economic literature is the Maximum Likelihood estimation algorithm, due to its robust numerical properties following the proposal by Evans (2005).

The canonical reference DFM can be described as follows:

$$x_t = C_0 f_t + e_t \qquad e_t \sim N(0, R) \tag{2}$$

$$f_t = \sum_{j=1}^{p} A_j f_{t-j} + u_t \qquad u_t \sim N(0, Q_0) \tag{3}$$

Where equation 2 is identified as the measurement equation and equation 3 as the transition equation, allowing the unobservable factor f_t to evolve as in a vector autoregressive model. These equations do not include trends or intercepts, as the included data must be stationary and standardized prior to estimation.

The matrix system is as follows:

x_t: a vector of $n \times 1$ observable time series at time $t : (x_t, ..., x_{nt})'$, which allows for missing data.

f_t: a vector of $r \times 1$ factors at time $t : (f_t, ..., f_{rt})'$.

C_0: a matrix of $n \times r$ observable time series with lag j.

Q_0: a matrix of $r \times r$ state covariances.

R: a matrix of $r \times r$ measurement covariances. This matrix is diagonal under the assumption that all covariances between the series are explained by the factors $E[x_{it} \mid x_{-i,t}, f_t] = c_{0i} f_t \forall i$, where c_{0i} is the $i - th$ row of C_0.

This model can be estimated using a classical form of the Kalman Filter and the Maximum Likelihood estimation algorithm, after transforming it into a State Space model. In a VAR expression, it would be as follows:

$$x_t = CF_t + e_t \qquad e_t \sim N(0, R) \tag{4}$$

$$F_t = AF_{t-1} + u_t \qquad u_t \sim N(0, Q) \tag{5}$$

3.3 Penalized Regression Models

These methodologies are employed to optimize the selection of predictor variables and control the model's complexity, which is crucial in preventing overfitting in high-dimensional settings. The literature suggests various forms of penalization to estimate the parameters β_j accurately. We will briefly explore the characteristics of the Ridge, Lasso, Elastic Net, and Adaptive Lasso models, emphasizing how these techniques allow for proper weighting of coefficients and how their application impacts the inclusion and relevance of variables in the final model.

3.3.1 Ridge Regression

The Ridge model is defined by adding a penalty based on the sum of squares of the coefficients of the predictor variables. This penalty compels the coefficients to be very small, preventing them from taking extremely high values, thus reducing the influence of less relevant variables. To estimate the coefficients $\hat{\beta}^{Ridge}$, the equation must be expressed as:

$$\min_{\beta}\left(\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\right) \tag{6}$$

Where y_i is the observed value of the dependent variable for observation i, x_{ij} is the value of predictor variable j in observation i, β_j is the coefficient associated with predictor variable j, p is the number of predictor variables, and λ is the regularization hyperparameter that controls the magnitude of the penalty. The sum of the terms β_j^2 in the penalty prevents the coefficients from reaching large values, thereby contributing to stability and reducing the risk of overfitting.

3.3.2 LASSO Regression

The LASSO (Least Absolute Shrinkage and Selection Operator) model, introduced by Tibshirani (1996), employs a penalty based on the sum of the absolute values of the coefficients of the predictor variables. This penalty has the property of forcing some coefficients to exactly reach zero, resulting in the automatic selection of a subset of more relevant predictor variables and the elimination of less significant ones. The Lasso coefficients $\hat{\beta}^{Lasso}$ are estimated:

$$\min_{\beta}\left(\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right) \tag{7}$$

Where the change lies in the hyperparameter λ which, by summing the absolute values of the coefficients $|\beta_j|$ in the penalty, leads to model selection and simplification by allowing some coefficients to be zero. This provides a more precise variable selection approach regarding the degree of importance of all variables.

3.3.3 Elastic Net Regression

The Elastic Net model appropriately combines the constraints of both the LASSO and Ridge models. In particular, Zou and Hastie (2005) mention that its advantage lies in correcting the model when the number of regressors exceeds the number of observations ($p > n$), which improves variable grouping. The penalty includes both the sum of the absolute values of the coefficients and the sum of the squares of the coefficients of the predictor variables. The equation for estimating the coefficients $\hat{\beta}^{Enet}$ is expressed as:

$$\min_{\beta}\left(\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}\left(\alpha|\beta_j| + (1-\alpha)\beta_j^2\right)\right) \tag{8}$$

where λ is the global regularization hyperparameter and α is the hyperparameter that controls the mix between Lasso ($\alpha = 1$) and Ridge ($\alpha = 0$) penalties. The combination of both penalties in the Elastic Net model allows for a higher degree of flexibility in variable selection and coefficient alignment.

3.3.4 Adaptive Lasso Regression

Following Zou (2006), the Adaptive LASSO model is a variant of the LASSO model that introduces a penalty approach which adaptively adjusts the magnitude of the penalties for each coefficient of the predictor variables. This adaptation allows for penalties to be different for different coefficients, potentially resulting in a more precise selection of relevant variables. Liu (2014), indicate that this process can be efficiently performed using the LARS algorithm. The equation for the Adaptive LASSO model ($\hat{\beta}^{AdL}$) is expressed as:

$$\min_{\beta}\left(\sum_{i=1}^{n}(y_i-\beta_0-\sum_{j=1}^{p}x_{ij}\beta_j)^2+\lambda\sum_{j=1}^{p}w_j|\beta_j|\right) \tag{9}$$

where λ is the regularization hyperparameter, and w_j is the adaptation factor for the coefficient β_j. It is important to note that the exact form of the adaptation factors w_j depends on the specific implementation and may vary. In general, these factors are calculated based on the absolute values of the coefficients in previous iterations of the algorithm.

3.4 Decision Tree Models

Decision Tree models are machine learning algorithms that represent decisions and actions in the form of a tree. In this case, we will present two algorithms where each internal node of the tree represents a feature or attribute, and each branch represents a decision or rule based on that attribute. The training data is divided based on these decisions until reaching leaf nodes, which correspond to the predictions, in our case, related to monthly GDP growth. Additionally, the use of these trees allows for an improvement in variable selection by handling non-linear relationships in the model.

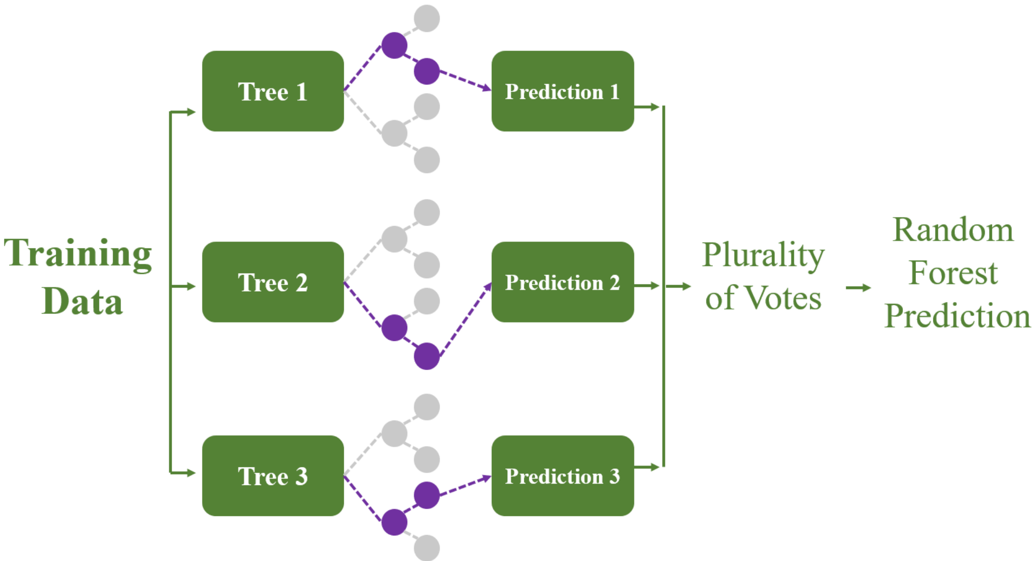
3.4.1 Random forest

This method is based on constructing decision trees using variables from a matrix X and a random selection of features. Additionally, it involves randomly selecting subsets of data from X with replacement to train each tree in the ensemble, distinguishing it from other tree-based techniques. Each tree generates a prediction of the target variable (in this case, monthly GDP), and the final model selects the most voted prediction in the ensemble of trees (Breiman, 2001). According to Tiffin (2016), Random Forest has the advantage of combining predictions from multiple trees and selecting those with lower error, thereby reducing the influence of potential individual errors (if the correlation between trees is low). In summary, this method recursively divides the data in X into optimized regions and uses variable-based criteria to forecast the target variable, then calculates the dependent variable as the average of these regions.

$$\hat{f}(x)=\sum_{m}\hat{c}_m I(x\in X_r);\hat{c}_m=avg(y_i|x_i\in X_r) \tag{10}$$

The algorithm has certain advantages, such as being efficient in handling large datasets with many variables, providing an estimation of variable importance, and offering an unbiased estimation of generalization error during its construction (Breiman, 2001). However, it has disadvantages like difficulty in interpreting results beyond predictions and a computationally intensive demand for training and hyperparameter tuning. Therefore, for this model, it was necessary to fine-tune it through cross-validation, achieving better performance on unseen data.

Figure 1: Simple Representation of the Random Forest Algorithm



Source: Own elaboration

3.4.2 Gradient Boosting Machine

"This algorithm builds a sequence of decision trees, where each tree is fitted to the residual errors of the previous tree. Therefore, each iteration obtains a new tree that minimizes the remaining error. These prediction models are trained using the errors from the accumulated set of weak predictions[1] in a way that provides a progressive improvement in regression performance compared to the initial model (Natekin and Knoll, 2013).

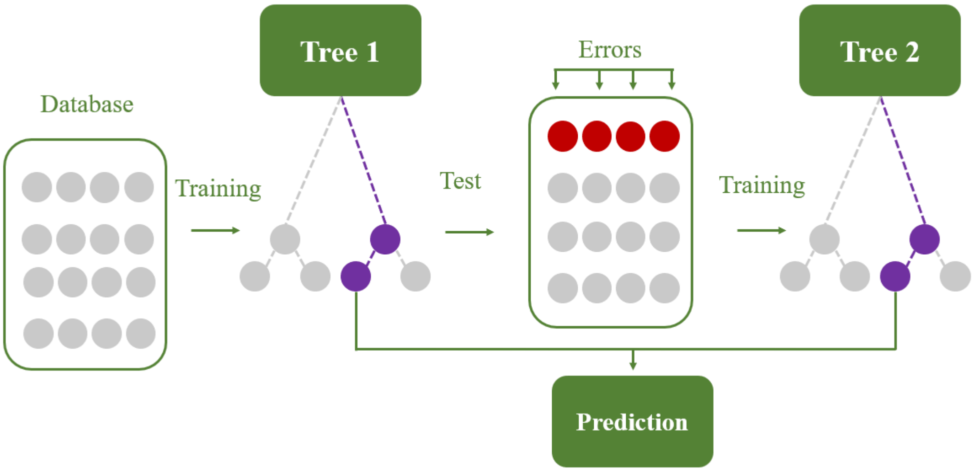
In essence, each tree in this algorithm contributes its prediction, which is added to the sequence of predictions from previous trees in order to enhance the final prediction of the model. Boehmke and Greenwell (2020), mention that this method can be summarized by the following equation.

$$F(x) = \sum_{z=1}^{Z} F_z(x) \tag{11}$$

where z is the number of trees that cumulatively add up the errors from all preceding trees. That is, the first tree $y = F_1(x)$, then the second tree will be $F_2(x) = F_1(x) + e_1$ and so on, successively, to minimize $F(x)$ as the following expression:

[1] Brownlee (2016), indicates that weak models do not necessarily mean they are better than accurate models, as they have the advantage of being able to correct the overfitting problem.

Figure 2: Simple Representation of the Gradient Boosting Machine Algorithm



Source: According to Boehmke and Greenwell (2020)

$$L = \sum_{z} L(y_z, F_z(x)) \tag{12}$$

Therefore, as new decision trees are incorporated, the accuracy of the final projection improves gradually, resulting in more precise forecasts for monthly GDP.

3.5 Data

The model's database comprises a variety of variables, ranging from macroeconomic and financial data to unstructured information related to sentiment or "trend" (See Tables 6, 7, and 8). This information set encompasses consumption indicators, such as credits, deposits, chicken sales, consumer surveys, and local activity indicators, including electricity production, hydrocarbons, economic expectations, and others. Investment indicators are also incorporated, such as internal cement consumption, capital goods imports, and so forth. A set of monetary indicators covering consumer and producer price indices, among others, is included. It is important to highlight the inclusion of sectoral variables related to fishing and agricultural production, which constitutes a unique feature compared to other nowcasting models. Furthermore, the database covers information on foreign trade, the labour market, and climate data.

In addition to conventional variables, we have incorporated unstructured data related to perception in various areas, such as the economy, consumption, labour market, politics, tourism, government support, and natural phenomena. These variables have the ability to capture the general sentiment of the population and its potential influence on economic indicators. In particular, the use of massive search engines, such as Google, stands out as a powerful tool for providing real-time information. Scott and Varian (2013), have pointed out that the inclusion of online searches as variables provides substantial benefits to short-term forecasting models, especially in detecting periods of high volatility. This is demonstrated in the ability to anticipate both the recession caused by the COVID-19 pandemic and the subsequent period of economic recovery. Consequently, the effectiveness of this approach has been widely investigated and adopted by central banks and international institutions. Thus, we estimate 10 groups (See Table 6) of variables that aim to track Google search queries, which are updated daily and can be downloaded from Google Trends. The selection of these words (variables) aims to convey different aspects of the economy, such as the consumption-related group, which is constructed based on searches for words like "Kia", "Restaurants", "Toyota", "Credits", "Loans", "Deals", "Mortgages", and "Cinema". Once this textual data is converted into numerical data, the inclusion of these series is evaluated in the estimations of an optimal model using Gibbs sampling following the findings of Garcia-Donato and Martinez-Beneito (2013) and using 50,000 iterations, an initial burning of 1,000 iterations, and constant beta priors (see Figure 10). This indicates that there is a high relevance of the group of unstructured variables such as the search frequency for "flights", "peruflight_us", "visa", or "El Niño", which would reflect the dynamics of tourism and climatic conditions, among others. Furthermore, we compare the results of this estimation with another one by reducing the sample to 2019 (see Figure 11), where unstructured data becomes more important when incorporating the pandemic period into the sample, which is in line with the findings of Richardson and Mulder (2018) and Woloszko (2020). Additionally, a contemporaneous correlation analysis of these variables against the monthly GDP is also performed, obtaining that more than 50% of the unstructured sample has a correlation greater than 30%.

The data frequency ranges from daily to monthly records in constructing the model. Each variable was assessed in terms of its predictive ability regarding monthly GDP growth. Then, to facilitate comparison and analysis, we transformed these variables into annualized monthly percentage changes and standardized them. This standardization process allows us to maintain a common reference framework and ensure that different variables contribute equitably to the model.

Ultimately, we have a total set of 91 predictors spanning from January 2008 to May 2023. The evaluation and selection of optimal predictors will be conducted independently for each machine learning algorithm employed. This approach will enable us to refine the process of choosing the most efficient prediction model, thereby achieving enhanced performance.

3.6 Strategy of the forecast evaluation

The method that will assess the accuracy in the projection of each model will be done through the root mean square error (RMSE), following the equation:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{13}$$

where y_t represents the observed value of monthly GDP growth, $\hat{y}_t$ is the forecasted value, and T is the total number of projections made. Following this initial assessment of prediction fit, we will employ the method proposed by Diebold and Mariano (1995) to determine if the projections generated by each machine learning model significantly differ from the *benchmark* model.

4 Results

This section begins by providing a brief description of the database training period, addresses hyper parameter optimization, and finish with a thorough analysis of the results.

4.1 Estimation and hyperparameters calibration

To estimate machine learning models, the selection of hyperparameters plays a crucial role in terms of efficiency and accuracy. The optimal determination of these values requires the split the sample data in three parts: i) a training set, ii) a validation set, and iii) testing set. Initially, the model is estimate with the training set (in-sample) where turns out the first set of hyperparameters. Then, the searching process of the optimal values that minimize the mean quadratic error of projections

(MSE[2]), through cross validation techniques. Once it is identified the optimal values, the accuracy of the model is evaluated in the testing set (*out-sample*).

Table 1: Strategy of testing estimations

Training dataset 2008m1-2014m08					**Testing set** 2014m09-2023m5
		⟷			↔
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	

Source: Own elaboration

Table 2: Priors and hyperparameter ranges

Model	Hyperparameter	Range	Optimised Value
Lasso	Lambda	0.001 to 0.009	0.007
Ridge	Lambda	0.01 to 0.09	0.310
Elastic Net	Alpha	0.1 to 0.9	0.500
	Lambda	0.01 to 0.09	0.040
Adaptive Lasso	Lambda	0.01 to 0.09	0.670
	Omega	0.1 to 0.9	0.340
Random Forest	#árboles	1 to 400	281
Gradient	# árboles	1 to 5000	19
Boosting	Distribución	Normal	Bernoulli
Machine	Shrinkage	0.001 to 0.009	0.300

Source: Own elaboration

Cross-validation method is used to calculate the best hyperparameters with the validation set. This process involves training and validation the concerning ML model in 5 folds, by using the every partition or fold as validation set and the others as training set on each iteration. Hence, we obtain 5 performance metrics, one by each fold, which are averaged.

[2]Indicator that measures the average of the squared errors between the predictions of a model and the real values, without applying the square root, used for validation of parameters in ML models.

Also, to identify the optimal hyperparameters, we will run the cross validation bayesian optimization algorithm, following closely Snoek, Larochelle, and Adams (2012).

In addition, to prevent overfitting in the ML models the hyperparameters are bounded within ranges recommended by the reviewed literature (See Zou and Hastie (2005)). This approach contributes significantly to the model's ability to make robust predictions, allowing for more effective exploration in estimating monthly GDP growth without the risk of overfitting.

4.2 Model comparison

Comparison of the prediction performance of the ML and benchmark models for the test set from September 2009 to May 2023 is presented in Table 3.

Table 3: Evaluation of model and benchmark forecasts
2014m09-2023m12

Model	RMSE	RMSE (Rel. to AR)	p-value
Lasso	0.26	0.79	0.014
Ridge	0.34	0.68	0.043
Elastic Net	0.28	0.55	0.039
Adaptive Lasso	0.68	0.71	0.126
Random Forest	0.45	0.76	0.089
Gradient Boosting Machine	0.17	0.21	0.016
Dynamic Factor Model	1.39	1.01	0.105
AR	2.55	0.00	

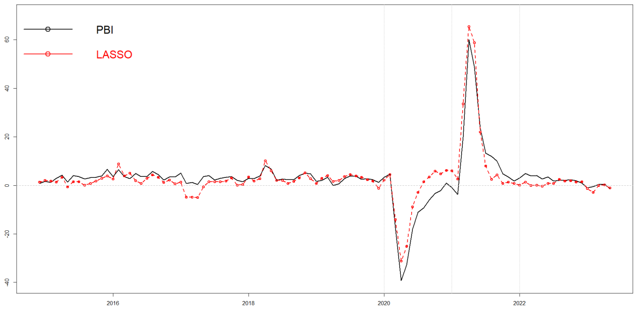
Source: Own elaboration

In terms of the forecast evaluation using the RMSE, the ML models manage to significantly minimize the projection error in comparison with the benchmark AR model and the dynamic factor model. Between the models that out stand over the others we get the *Gradient Boosting Machine*, *LASSO* and *Elastic Net* that achive to reduce the forecast error around 20% to 25%. Also, Diebold-Mariano statistic [3] concludes that most of the ML models are statistically significant, in line with previous research. (Richardson and Mulder, 2018; H. Varian, 2014; Q. Zhang, Ni, and Xu, 2023).

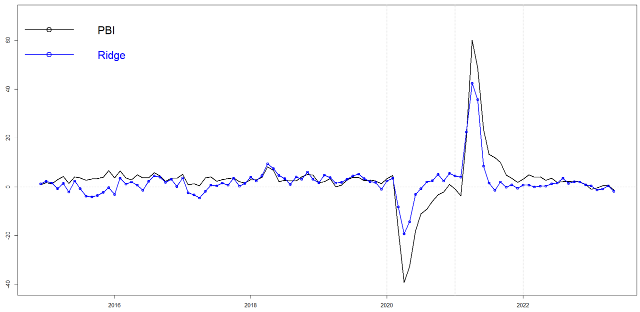
On the other hand, it is important to highlight that real-time forecasts presented in this document successfully anticipated the economic contraction caused by the COVID-19 pandemic in March 2020 in the Peruvian context, and also accurately captured the subsequent economic recovery period in March of the following year, which supports the usefulness and effectiveness of using penalty models and/or decision trees to forecast economic variables.

[3] Diebold and Mariano (1995)

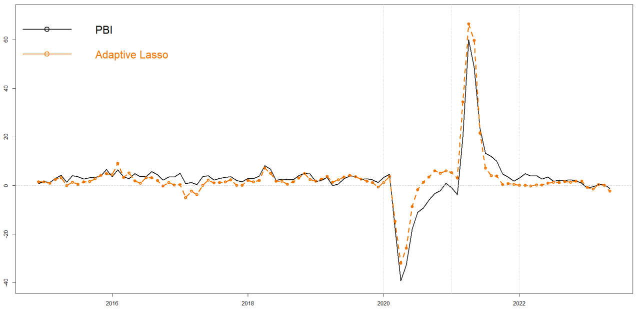
Figure 3: ML model projection and GDP



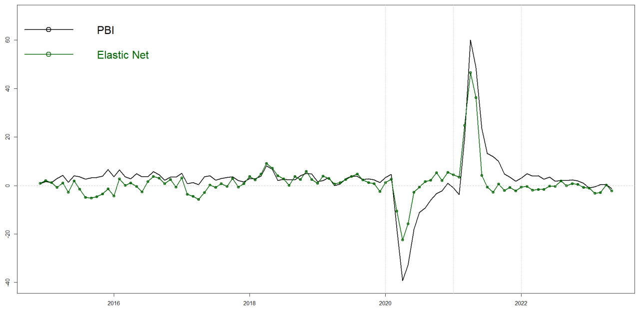
(a) LASSO and GDP



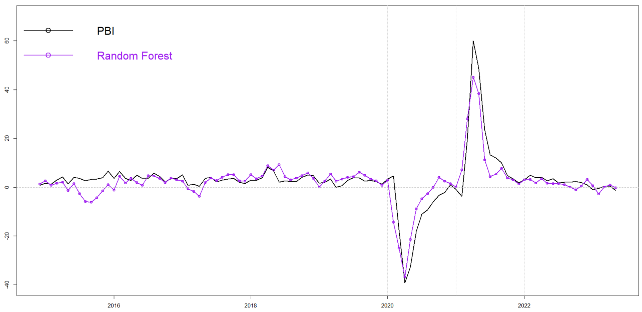
(b) Ridge and GDP



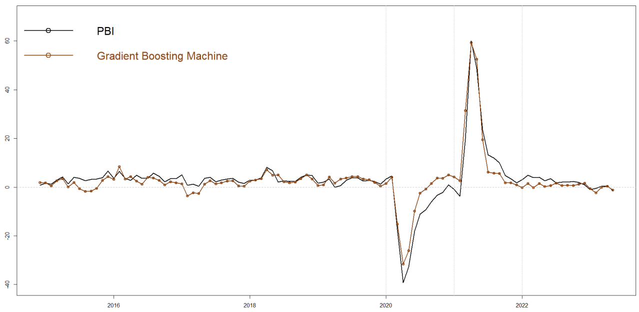
(c) Adaptive LASSO and GDP



(d) Elastic Net and GDP



(e) Random Forest and GDP



(f) Gradient Boosting Machine and GDP

4.3 Consistency

To test the consistency of the results and determine if the ML model projections contribute positively to the accuracy predictions of monthly GDP over the benchmarks models, we use the C. Romer and D. Romer (2008) approach, but instead of using a officials prediction, we replace to a DFM estimation that incorporate the electricity as main leading indicator, which popular among Economic Studies Department in Peru. We estimate the following regression model:

$$y_t = \beta_1 DFME_t + \beta_2 ML_{it} + e_t \tag{14}$$

Where y_t represents the real monthly GDP growth, $DFME_t$ is the dynamic factor model estimated with electricity production and ML_i is the out-sample prediction for each machine learning model. The results obtained indicate that all the projections of machine learning contribute significantly to the GDP projection, with the best model being the *Gradient Boosting Machine* according to the Akaike criterion. Likewise, analyzing the estimation errors of the models generated by the equation 14, we applied the test proposed by Harvey, Leybourne, and Newbold (1997) with a long run variance autocorrelation estimator from Diebold and Mariano (1995), to evaluate the fit gains in the estimates by including the results of the ML models. The $p - value$ are shown in the last column of the table 4, where the alternative hypothesis is that the models in equation 14, which include the ML model projection, are more accurate than the predictions under the dynamic factor model alone. These values indicate a superior accuracy of the models incorporating Machine Learning at 10% confidence level in the case of, but at 5% in the others.

Table 4: β_2^e value and validation criteria

Models	Estimated value	AIC	p-value	p-value (DM)
Lasso	0.714	520.32	0.000	0.079
Ridge	0.936	554.73	0.000	0.057
Elastic Net	0.839	549.80	0.000	0.055
Adaptive Lasso	0.703	517.49	0.000	0.046
Random Forest	0.783	534.20	0.000	0.049
Gradient Boosting Machine	0.810	492.09	0.000	0.041

Source: Own elaboration

5 Conclusions

In this article, we evaluated the prediction accuracy of the most popular Machine Learning algorithms to do the nowcasting of the monthly growth rate of Peruvian GDP. The analysis window was between 2008 and 2023 and works with several leading indicators to assess the dynamic of the GDP's components measured by the expenditure and productive sector approach. Furthermore, it is worth mentioning that we have enriched our approach by incorporating a sentiment data index built through Google Trends, that shown to be helpful to predict in advance economic activity. In fact, the Machine Learning approach allows the use of 91 variables simultaneously between structured data and no structured data, one of the documents that use a larger dataset used for the Peruvian GDP prediction case. The evaluation results and consistency exercise show evidence of the positive contribution of ML models and sentiment data improve significantly the model accuracy and allow the early detection of periods of high volatility, an aspect that conventional models often fail to capture.

Our results shed light on outperforming the machine learning over the AR and DFM models in prediction accuracy, which opens a new approach agenda on improvements in the forecast of relevant macroeconomic variables such as consumption, employment, and investment, among others.

In fact, as a pending agenda regard, we can point out three issues. First, the need to analyze the marginal prediction gains from the inclusion of unstructured data in reducing forecast error. Since our results have shown improvements in the accuracy. One question arises. Would the analyzed period between influence those results given that between 2004 and 2023 includes high volatility events such as the pandemic, the global financial crisis and various climate shocks in 2017 and 2023, where ML models with data do not structured ones gain greater predictive capacity by being able to track daily frequency data from Google Trend searches. This could be achieved by performing a variance analysis of the projection errors comparing ML models with other more traditional ones during a period of relative normality and other periods of crisis. Second, a fact we observed in the estimates of the unsynchronized availability of the variables (91), which represented challenges and difficulties, which raises the question of whether consistent results are equally obtained with a smaller number of variables, we estimate this in roughly 45% of the 91 variables of the dataset. This proportion could be evaluated in subsequent studies reducing the software requirements. Third, the treatment of the unstructured data could be improve. In this document we use a simple and didactic managing of no-structured data, but it might be consider monthly weighteing of searched words in GoogleTrend to smooth the high variability related to this type of data.

References

Armstrong (2001). *Principles of forecasting: a handbook for researchers and practitioners*. Vol. 30. Springer.

Aruoba, S Borağan, Diebold, Francis X, and Scotti, Chiara (2009). "Real-time measurement of business conditions". In: *Journal of Business & Economic Statistics* 27(4), pp. 417–427.

Athey, Susan (2018). "The impact of machine learning on economics". In: *The economics of artificial intelligence: An agenda*. University of Chicago Press, pp. 507–547.

Athey, Susan and Markus, M (2017). "Mobius, and Jeno Pál". In: *The impact of aggregators on internet news consumption*.

Bańbura, Marta, Giannone, Domenico, et al. (2013). "Now-casting and the real-time data flow". In: *Handbook of economic forecasting*. Vol. 2. Elsevier, pp. 195–237.

Bańbura, Marta and Rünstler, Gerhard (2011). "A look into the factor model black box: publication lags and the role of hard and soft data in forecasting GDP". In: *International Journal of Forecasting* 27(2), pp. 333–346.

Barrios, Juan José et al. (2021). "Nowcasting para predecir actividad económica en tiempo real: los casos de Belice y El Salvador". In.

Blei, David M, Ng, Andrew Y, and Jordan, Michael I (2003). "Latent dirichlet allocation". In: *Journal of machine Learning research* 3(Jan), pp. 993–1022.

Boehmke, Bradly and Greenwell, BM (2020). "Chapter 12: Gradient Boosting". In: *Hands-On Machine Learning with R*.

Bok, Brandyn et al. (2018). "Macroeconomic nowcasting and forecasting with big data". In: *Annual Review of Economics* 10, pp. 615–643.

Breiman, Leo (2001). "Random forests". In: *Machine learning* 45, pp. 5–32.

Brownlee, Jason (2016). "Bagging and random forest ensemble algorithms for machine learning". In: *Machine Learning Algorithms*, pp. 4–22.

Diebold, Francis X and Mariano, Roberto S (1995). "Comparing predictive accuracy". In: *Journal of Business and Economic Statistics* 13(3), pp. 253–263.

Döpke, Jörg, Fritsche, Ulrich, and Pierdzioch, Christian (2017). "Predicting recessions with boosted regression trees". In: *International Journal of Forecasting* 33(4), pp. 745–759.

Doz, Catherine, Giannone, Domenico, and Reichlin, Lucrezia (2012). "A quasi–maximum likelihood approach for large, approximate dynamic factor models". In: *Review of economics and statistics* 94(4), pp. 1014–1024.

Eberendu, Adanma Cecilia et al. (2016). "Unstructured Data: an overview of the data of Big Data". In: *International Journal of Computer Trends and Technology* 38(1), pp. 46–50.

Einav, Liran and Levin, Jonathan (2014). "The data revolution and economic analysis". In: *Innovation Policy and the Economy* 14(1), pp. 1–24.

Escobal D'Angelo, Javier and Torres, Javier (2002). "Un sistema de indicadores lideres del nivel de actividad para la economía peruana". In.

Etter, Richard, Graff, Michael, et al. (2011). *A composite leading indicator for the Peruvian economy based on the BCRP's monthly business tendency surveys*. Tech. rep. Banco Central de Reserva del Perú.

Evans, Martin (2005). *Where are we now? real-time estimates of the macro economy*.

Forero, Fernando J Perez, Aguilar, Omar J Ghurra, and Vargas, Rodrigo F Grandez (2016). "Un Indicador Lider de Actividad Real para el Perú". In.

Garcia-Donato, Gonzalo and Martinez-Beneito, Miguel A (2013). "On sampling strategies in Bayesian variable selection problems with large model spaces". In: *Journal of the American Statistical Association* 108(501), pp. 340–352.

Ghosh, Saurabh and Ranjan, Abhishek (2023). "A Machine Learning Approach To Gdp Nowcasting: An Emerging Market Experience". In: *Buletin Ekonomi Moneter dan Perbankan* 26, pp. 33–54.

Giannone, Domenico, Reichlin, Lucrezia, and Small, David (2008). "Nowcasting: The real-time informational content of macroeconomic data". In: *Journal of monetary economics* 55(4), pp. 665–676.

Giglio, Stefano, Kelly, Bryan, and Xiu, Dacheng (2022). "Factor models, machine learning, and asset pricing". In: *Annual Review of Financial Economics* 14, pp. 337–368.

Green, Kesten C and Armstrong, Scott (2015). "Simple versus complex forecasting: The evidence". In: *Journal of Business Research* 68(8), pp. 1678–1685.

Harvey, David, Leybourne, Stephen, and Newbold, Paul (1997). "Testing the equality of prediction mean squared errors". In: *International Journal of forecasting* 13(2), pp. 281–291.

Kant, Dennis, Pick, Andreas, and Winter, Jasper de (2022). "Nowcasting GDP using machine learning methods". In.

Kapsoli Salinas, Javier and Bencich Aguilar, Brigitt (2002). "Indicadores lideres, redes neuronales y predicción de corto plazo". In.

Liu, Zi Zhen (2014). *The doubly adaptive LASSO methods for time series analysis*. The University of Western Ontario (Canada).

Longo, Luigi, Riccaboni, Massimo, and Rungi, Armando (2022). "A neural network ensemble approach for GDP forecasting". In: *Journal of Economic Dynamics and Control* 134, p. 104278.

Makridakis, Spyros, Spiliotis, Evangelos, and Assimakopoulos, Vassilios (2018). "Statistical and Machine Learning forecasting methods: Concerns and ways forward". In: *PloS one* 13(3), e0194889.

Martınez, M and Quineche, R (2014). *Un indicador lıder para el nowcasting de la actividad económica del perú*. Tech. rep. Mimeo.

Medeiros, Marcelo C et al. (2021). "Forecasting inflation in a data-rich environment: the benefits of machine learning methods". In: *Journal of Business & Economic Statistics* 39(1), pp. 98–119.

Muchisha, Nadya Dwi et al. (2021). "Nowcasting Indonesia's GDP Growth Using Machine Learning Algorithms". In: *Indonesian Journal of Statistics and Its Applications* 5(2), pp. 355–368.

Natekin, Alexey and Knoll, Alois (2013). "Gradient boosting machines, a tutorial". In: *Frontiers in neurorobotics* 7, p. 21.

Pérez Forero, Fernando (2018). *Nowcasting peruvian gdp using leading indicators and bayesian variable selection*. Tech. rep. Banco Central de Reserva del Perú.

Richardson, Adam and Mulder, Thomas (2018). "Nowcasting New Zealand GDP using machine learning algorithms". In.

Romer, Christina and Romer, David (2008). "The FOMC versus the staff: where can monetary policymakers add value?" In: *American Economic Review* 98(2), pp. 230–235.

Scott, Steven L and Varian (2013). *Bayesian Variable Selection for Nowcasting Economic Time Series*. Tech. rep. National Bureau of Economic Research.

Snoek, Jasper, Larochelle, Hugo, and Adams, Ryan P (2012). “Practical bayesian optimization of machine learning algorithms”. In: *Advances in neural information processing systems* 25.

Stock, James H and Watson, Mark W (1989). “New indexes of coincident and leading economic indicators”. In: *NBER macroeconomics annual* 4, pp. 351–394.

Suphaphiphat, Nujin, Wang, Yifei, and Zhang, Hanqi (2022). “A Scalable Approach Using DFM, Machine Learning and Novel Data, Applied to European Economies”. In.

Tibshirani, Robert (1996). “Regression shrinkage and selection via the lasso”. In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58(1), pp. 267–288.

Tiffin, Mr Andrew (2016). *Seeing in the dark: A machine-learning approach to nowcasting in Lebanon*. International Monetary Fund.

Varian, Hal (2014). “Machine Learning and Econometrics”. In: *Slides package from talk at University of Washington*.

Woloszko, Nicolas (2020). *A Weekly Tracker of activity based on machine learning and Google Trends*.

Zhang, Qin, Ni, He, and Xu, Hao (2023). “Nowcasting Chinese GDP in a data-rich environment: Lessons from machine learning algorithms”. In: *Economic Modelling* 122, p. 106204.

Zou, Hui (2006). “The adaptive lasso and its oracle properties”. In: *Journal of the American statistical association* 101(476), pp. 1418–1429.

Zou, Hui and Hastie, Trevor (2005). “Regularization and variable selection via the elastic net”. In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 67(2), pp. 301–320.

6 Appendix

Table 5: Literature on Nowcasting

Author	Year	Methodology	Country
International			
Nowcasting			
Author	**Year**	**Methodology**	**Country**
Banbura and others	2013	DFM	Europe
Evans	2005	DFM	US
Giannone and others	2008	DFM	US
Nowcasting with machine learning			
Richardson and others	2018	Various models ML	New Zealand
Giannone and others	2008	DFM	US
Ghosh and Ranjan	2023	various ML	India
Muchisha and others	2020	various ML vs DFM	Indonesia
Zhang, Ni and Xu	2023	various ML	China
Kant and others	2022	various ML	Netherlands
Suphaphiphat and others	2022	various ML	Europe
Nowcasting with big data			
Blei, Ng and Jordan	2003	LDA	US
Athey, Mobius and Pal	2017	Google News	Spain
Woloszko	2020	Google Trends	USA
Niesert and otros	2020	Google Trends	Advanced Economies
Peruvian main references			
Escobal and Torres	2002	DFM	Peru
Forero	2016	DFM	Peru
Kapsoli and Bencich	2002	Neuronal Networks	Peru
Forero	2018	Bayesian VAR	Peru
Etter and Graff	2011	Surveys	Peru
Martinez and Quineche	2014	Neuronal Networks	Peru

Source: Own elaboration

Table 6: List of no structured variables included in the model

Unstructured variable details		
Units of Measure	**Frequency**	**Source**
Search Index (0 to 100)	Daily	Google Trends
Variables		
1.- Searched Words on Economic		
Inflación	Recesión	
2.- Searched Words on Consumption		
kia	toyota	Cinema
Restaurantes	Créditos	Préstamos
Hipotecarios	Ofertas	
3.- Searched Words on Labor Market		
Empleo	Desempleo	Trabajo
4.- Searched Words on Sectorial Industry		
Minería	Inversión	
5.- Searched Words on Current Situation		
Crisis Perú	Quiebra	Economía
Crisis económica		
6.- Searched Words on Real Estate Market		
Terrenos	Inmuebles	
7.- Searched Words on Politics		
Elecciones		
8.- Searched Words on Tourism		
Viajes	Machu Picchu	Vuelos
Visa	Vuelos a Estados Unidos	Alojamientos
Hoteles	Vacaciones	
9.- Searched Words on Bonds and Pensions		
Bonos	CTS	AFP
10.- Searched Words on Weather and Natural Phenomena		
Lluvias	Fenómeno el Niño	Sequías
Heladas	Huaico	

Source: Own elaboration

Table 7: List of structured variables included in the model (a)

No.	Variable	Units of Measure	Frequency	Source
	Main Indicator			
1	GDP	Index 2007 = 100	Monthly	INEI
	Consumption Indicators			
2	Credit	S/ Millions	Monthly	BCRP
3	Credit	US$ Millions	Monthly	BCRP
4	Credit (constant exchange rate)	S/ Millions	Monthly	BCRP
5	Consumer credits	S/ Millions	Monthly	BCRP
6	Mortgage Loans	S/ Millions	Monthly	BCRP
7	Deposits	S/ Millions	Monthly	BCRP
8	Deposits	S/ Millions	Monthly	BCRP
9	Sales of chickens	Metric Tons	Daily	MIDAGRI
10	Consumer Confidence Index	Points	Monthly	Apoyo Consultoria
	Activity Indicators			
11	Electricity Production		Monthly	INEI
12	Hydrocarbon Production		Daily	MINEM
13	3-Month Economic Expectations	Points	Monthly	BCRP
14	Oil	B/D	Daily	MINEM
15	Natural Gas	MCF	Daily	MINEM
	Investment Indicators			
16	Domestic Cement Consumption	Index	Weekly	INEI
17	Import of Intermediate Inputs	Index	Weekly	INEI
18	Import of Capital Goods	Index	Weekly	INEI
	Labor Market Indicators			
19	Employed Labor Force	Thousands	Monthly	INEI
20	Properly Employed Population [4]	Thousands	Monthly	INEI
	Public Investment Indicators			
21	Non-Financial Gov. Expenditures	S/ Millions	Monthly	BCRP
22	IAFO	Index	Monthly	INEI
	Foreign Trade Indicators			
23	Volume of Imported Inputs	Index	Monthly	INEI
24	Terms of Trade	Index	Monthly	BCRP
25	IPX	Index	Monthly	BCRP
26	IPM	Index	Monthly	BCRP
	Finacial Indicators			
27	General Stock Market Index[5]	Percentages	Daily	Bloomberg
28	Liquidity	Millions of Soles	Monthly	BCRP
	Monetary Indicators			
29	CPI	Index	Monthly	INEI
30	Non Food and Energy Price Index	Index	Monthly	BCRP
31	Wholesale Price Index	Index	Monthly	BCRP
32	Core CPI	Index	Monthly	BCRP

Source: Own elaboration

Table 8: List of structured variables included in the model(b)

Structured variables				
International Indicators				
33	Multilateral Real Exchange Rate	(2009=100)	Monthly	BCRP
34	EMBIG Perú	Pbs	Daily	BCRP
35	Oil WTI	Dollars per Barrel	Daily	Bloomberg
36	USIPC	Index	Monthly	FRED
37	Industrial Production Index	YoY	Quarterly	Bloomberg
38	Copper	cUS$/lb.	Daily	Bloomberg
39	Gold	US$/oz.tr.	Daily	Bloomberg
40	US Manufacturing PMI	Points	Monthly	Bloomberg
41	FED Interest Rate (Upper Limit)	Percentages	Monthly	Bloomberg
42	VIX Index	Percentages	Daily	Bloomberg
43	Spread 2Y-5Y		Monthly	Bloomberg
44	China Industrial Production	YoY	Monthly	Bloomberg
45	PPI by All Commodities	(1982=100)	Monthly	FRED
Climate Indicators				
46	ATSM	Degrees Celsius	Monthly	IMARPE
Fishery Indicators				
47	Anchoveta Landing	Metric Tons	Daily	IMARPE
48	Logarithm of Anchoveta Landing		Daily	Own elaboration
49	Anchoveta Landing[6]		Daily	Own elaboration
50	Variation Anchoveta Landing[7]		Daily	Own elaboration
Agricultural Indicators				
51	Paddy Rice production	Tons	Monthly	MIDAGRI
52	Potato production	Tons	Monthly	MIDAGRI
53	Onion production	Tons	Monthly	MIDAGRI
54	Tomato production	Tons	Monthly	MIDAGRI

Source: Own elaboration

[4]Metropolitan Lima
[5]Lima
[6]Seasonally Adjusted
[7]Seasonally Adjusted

Figure 4: Gibb sampling (2004-2023) - probability of inclusion in optimal model

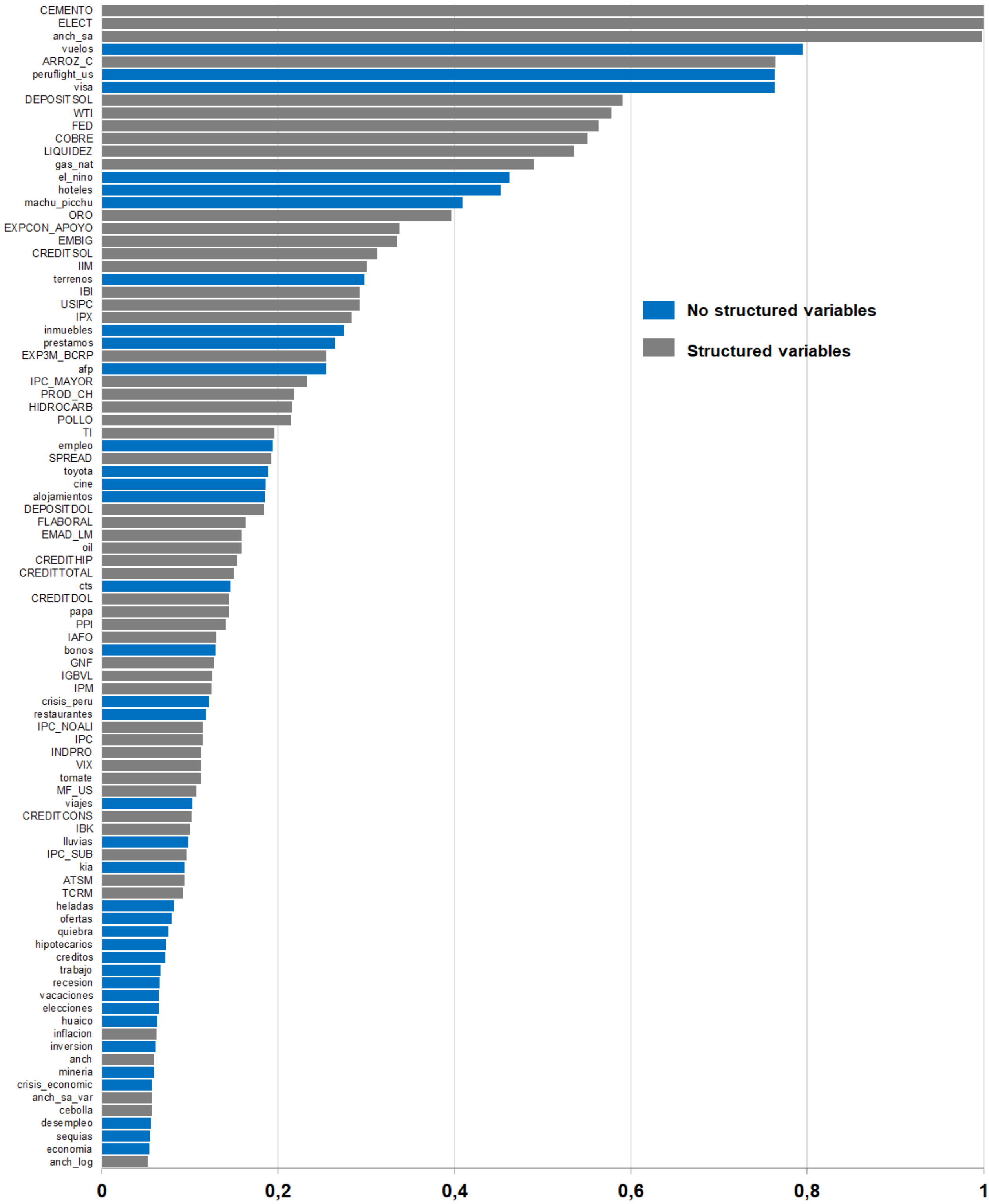


Figure 5: Gibb sampling (2004-2019) - probability of inclusion in optimal model

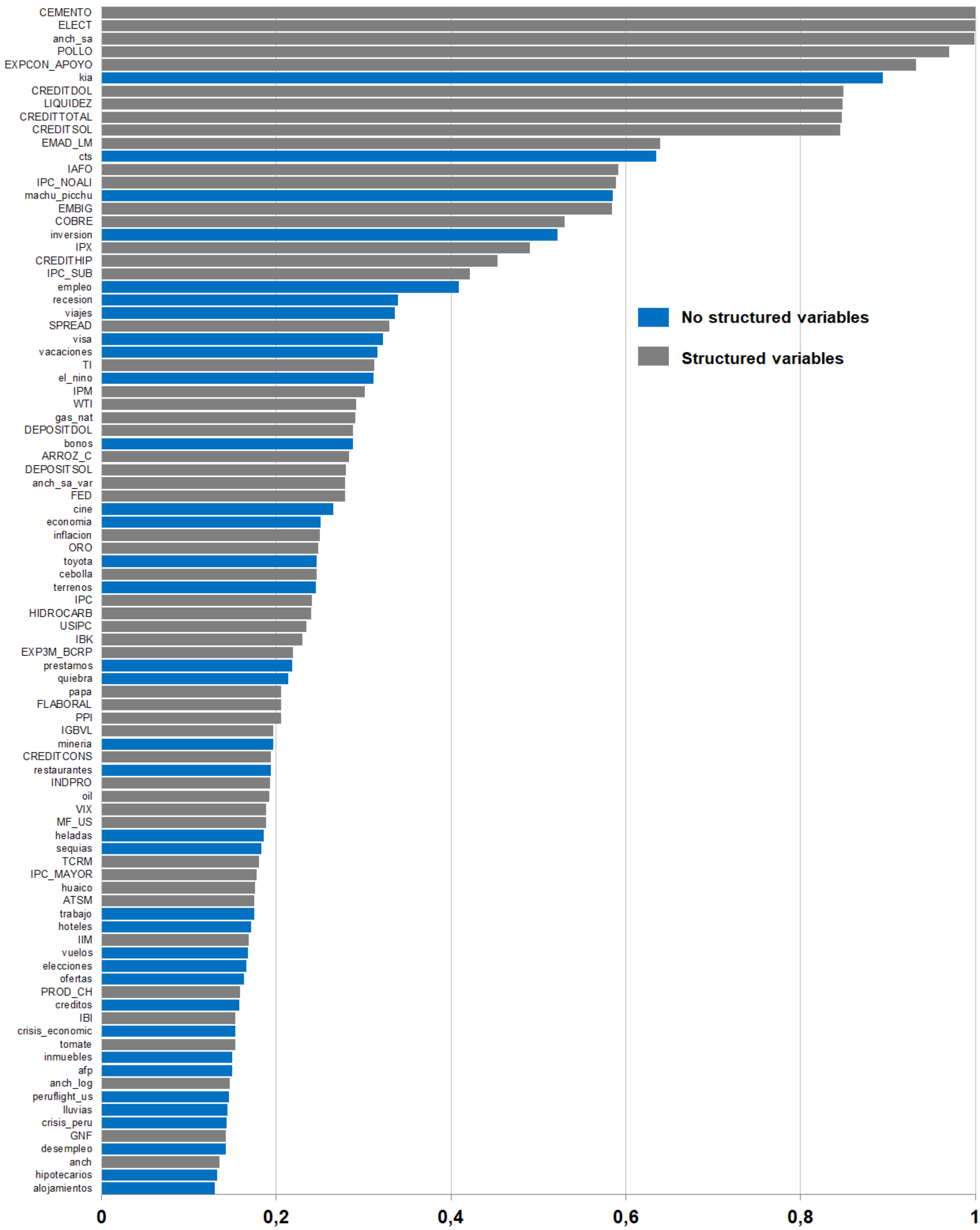
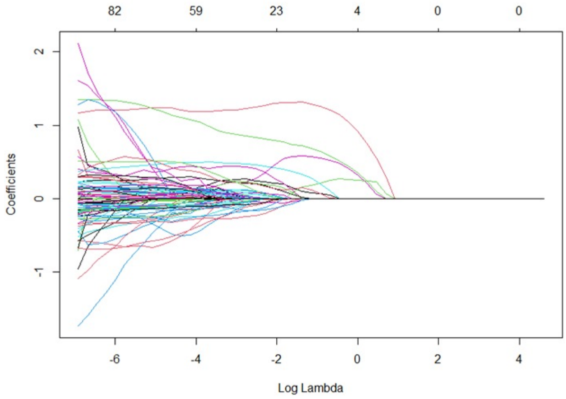


Figure 6: LASSO Optimal Parameters

(a) Coef. (e) by hyperparameter range



(b) Optimal hyperparameter vs. MSE

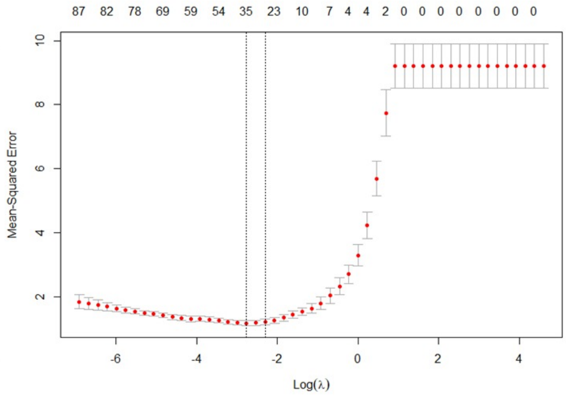
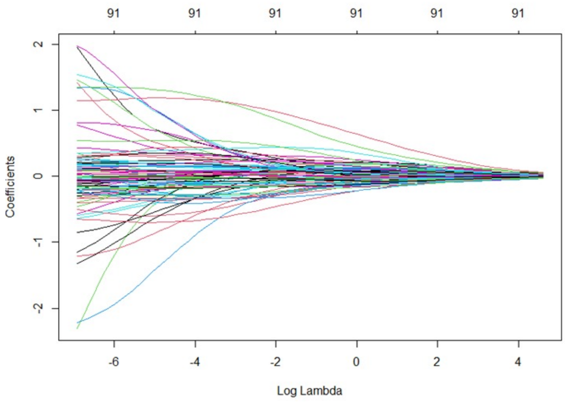


Figure 7: Ridge Optimal Parameters

(a) CCoef. (e) by hyperparameter range



(b) Optimal hyperparameter vs. MSE

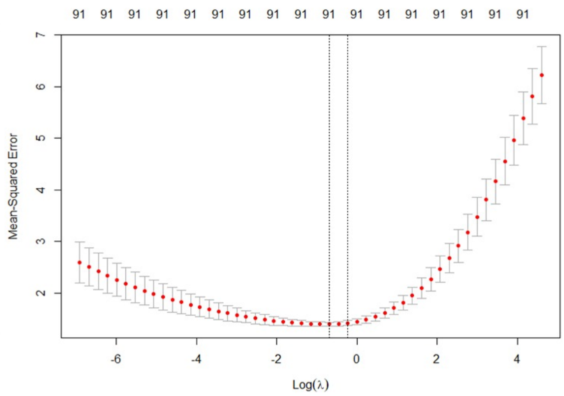


Figure 8: Elastic Net Optimal Parameters

(a) Coef. (e) by hyperparameter range (b) Optimal hyperparameter vs. MSE

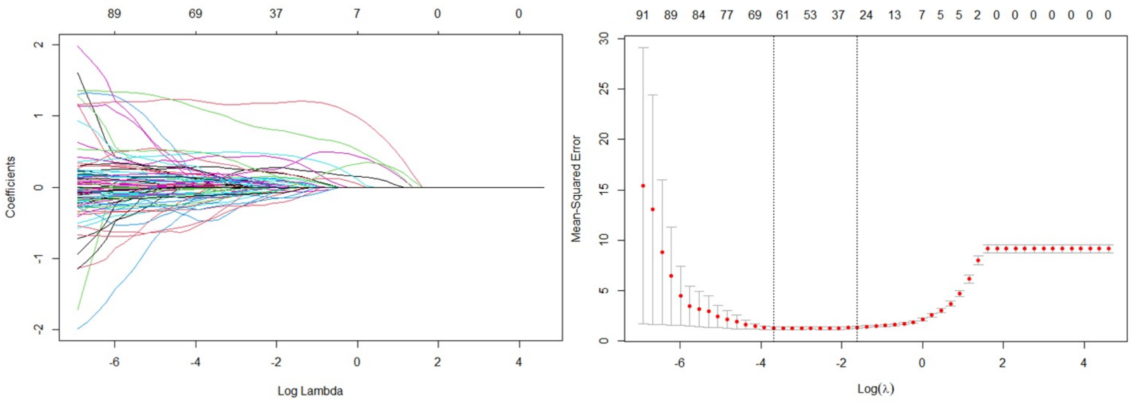


Figure 9: Adaptive LASSO Optimal Parameters

(a) Coef. (e) by hyperparameter range (b) Optimal hyperparameter vs. MSE

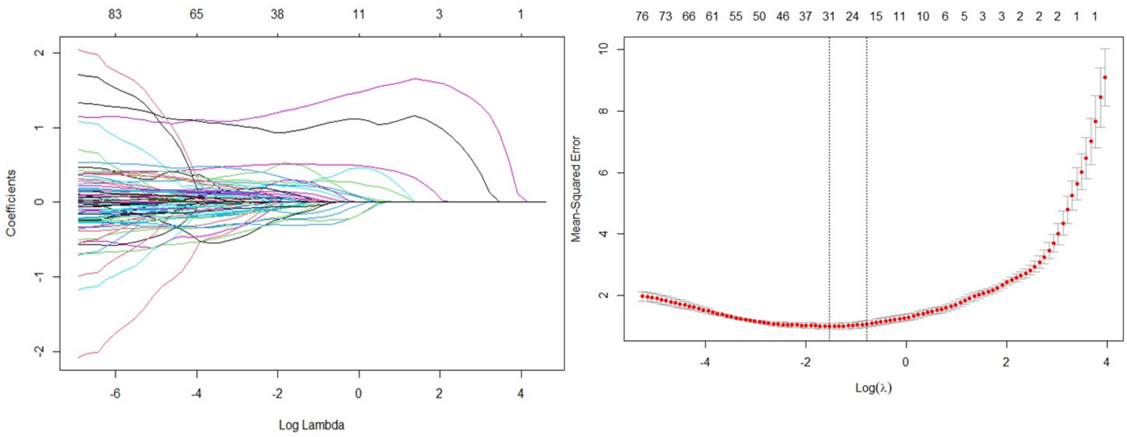


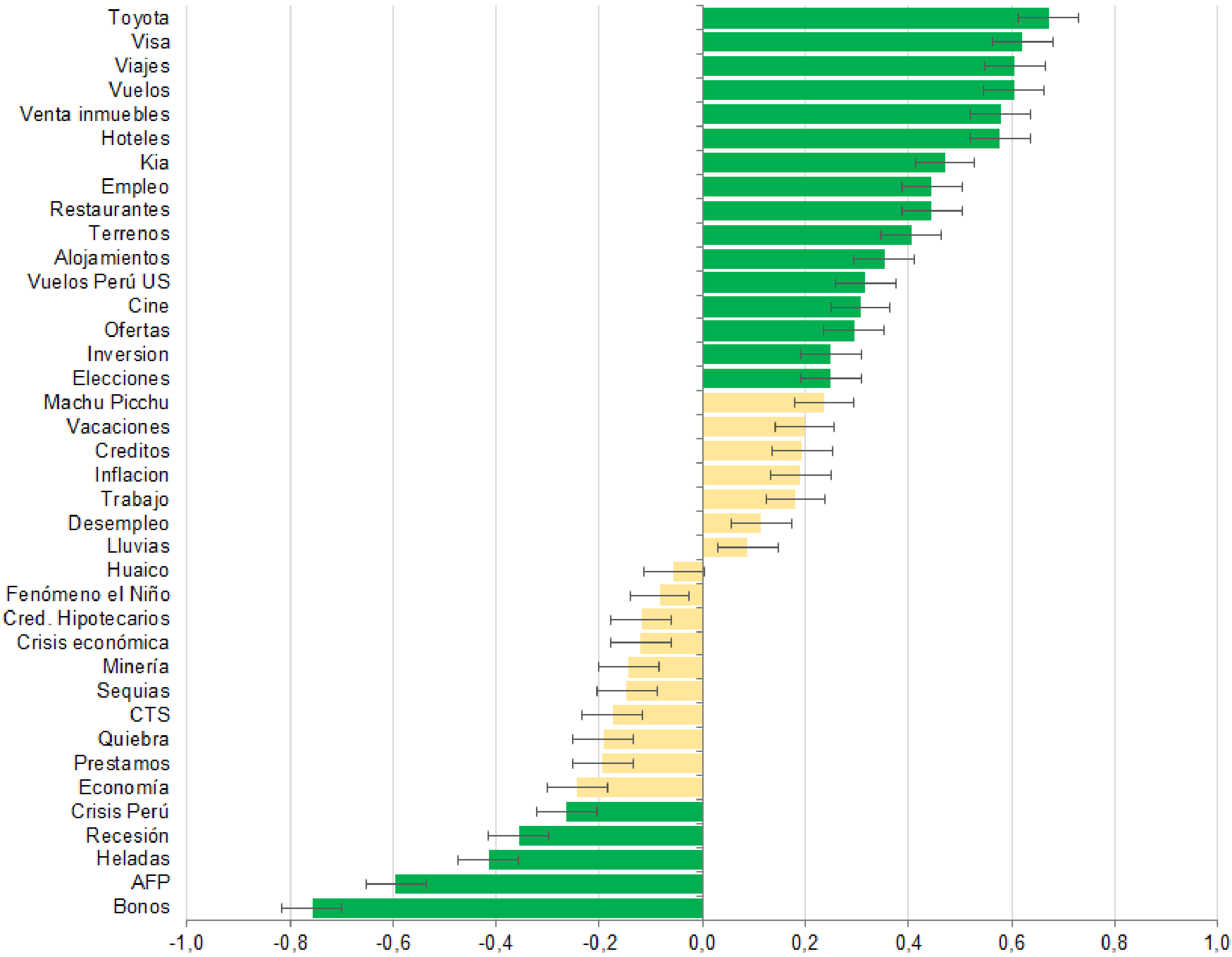
Figure 10: Dynamic correlations of the main variables

N°	Variables	Time						
		t-3	t-2	t-1	t	t+1	t+2	t+3
1	ELECT	0,5	0,6	0,6	0,8	0,6	0,5	0,4
2	IBK	0,5	0,6	0,7	0,7	0,7	0,8	0,7
3	DEPOSITSOL	0,6	0,6	0,6	0,7	0,7	0,7	0,6
4	CEMENTO	0,6	0,6	0,6	0,7	0,5	0,5	0,4
5	IIM	0,6	0,6	0,6	0,7	0,5	0,5	0,4
6	CREDITCONS	0,4	0,4	0,5	0,6	0,6	0,7	0,7
7	PPI	0,5	0,5	0,6	0,6	0,6	0,5	0,5
8	IPM	0,5	0,5	0,6	0,6	0,5	0,5	0,4
9	CREDITTOTAL	0,3	0,4	0,5	0,6	0,6	0,6	0,6
10	IPC_MAYOR	0,2	0,3	0,4	0,5	0,6	0,6	0,6
11	gas_nat	0,3	0,4	0,4	0,5	0,5	0,5	0,5
12	PROD_CH	0,6	0,6	0,6	0,5	0,4	0,4	0,3
13	CREDITDOL	0,4	0,4	0,5	0,5	0,5	0,5	0,5
14	EXP3M_BCRP	0,6	0,6	0,5	0,5	0,4	0,3	0,2
15	USIPC	0,4	0,4	0,5	0,5	0,5	0,4	0,4
16	IBI	0,6	0,5	0,5	0,5	0,4	0,3	0,3
17	LIQUIDEZ	0,2	0,2	0,3	0,5	0,5	0,6	0,6
18	WTI	0,5	0,5	0,5	0,4	0,4	0,3	0,3
19	ORO	0,5	0,4	0,4	0,4	0,3	0,3	0,2
20	IPX	0,5	0,5	0,4	0,4	0,3	0,2	0,1
21	EMAD_LM	0,4	0,4	0,4	0,4	0,3	0,3	0,2
22	INDPRO	0,4	0,4	0,4	0,4	0,3	0,2	0,2
23	MF_US	0,4	0,4	0,4	0,4	0,3	0,2	0,2
24	CREDITHIP	0,3	0,3	0,3	0,4	0,4	0,4	0,5
25	GN	0,4	0,4	0,3	0,3	0,2	0,1	0,1
26	FLABORAL	0,4	0,4	0,4	0,3	0,3	0,2	0,1
27	CREDITSOL	0,1	0,2	0,3	0,3	0,4	0,4	0,4
28	IAFO	0,1	0,2	0,1	0,3	0,2	0,2	0,2
29	anch_sa	0,1	0,0	0,1	0,3	0,1	0,1	0,0
30	COBRE	0,4	0,4	0,3	0,3	0,2	0,1	0,0
31	IPC	-0,1	0,0	0,1	0,2	0,3	0,4	0,4
32	HIDROCARB	-0,1	0,0	0,0	0,2	0,1	0,2	0,2
33	VIX	0,0	0,1	0,1	0,2	0,2	0,3	0,3
34	anch	0,0	0,0	0,0	0,2	0,1	0,1	0,0
35	tomate	0,1	0,1	0,2	0,1	0,2	0,2	0,1
36	anch_log	0,1	0,1	0,1	0,1	0,1	0,1	0,1
37	TI	0,3	0,3	0,2	0,1	0,0	-0,1	-0,2
38	ARROZ_C	-0,1	-0,1	0,0	0,1	0,0	0,0	0,1
39	FED	0,0	0,0	0,1	0,1	0,0	0,0	0,0
40	cebolla	0,2	0,2	0,1	0,0	0,1	0,0	0,0
41	oil	-0,2	-0,2	-0,1	0,0	-0,1	0,1	0,1
42	POLLO	0,1	0,1	0,1	0,0	0,0	-0,1	-0,1
43	papa	0,0	0,0	0,0	0,0	0,0	-0,1	0,0
44	IGBVL	0,2	0,1	0,1	0,0	-0,1	-0,1	-0,2
45	EMBIG	0,2	0,1	0,0	-0,1	-0,1	-0,2	-0,2
46	EXPCON_APOYO	0,1	0,0	-0,1	-0,1	-0,2	-0,2	-0,2
47	IPC_SUB	-0,3	-0,2	-0,2	-0,1	0,0	0,1	0,2
48	TCRM	-0,2	-0,2	-0,1	-0,1	-0,1	-0,1	-0,1
49	anch_sa_var	-0,1	-0,1	-0,2	-0,1	-0,2	-0,1	-0,2
50	SPREAD	-0,1	-0,2	-0,1	-0,1	-0,1	-0,1	-0,1
51	DEPOSITDOL	-0,3	-0,3	-0,3	-0,2	-0,1	0,0	0,0
52	ATSM	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2	-0,2
53	IPC_NOALI	-0,6	-0,6	-0,5	-0,5	-0,4	-0,3	-0,2

High correlation   Low correlation

Source: Own elaboration

Figure 11: Correlations of the main nonstructured variables



Source: Own elaboration