Macroeconomic Forecasting of French Economy using Machine Learning Approach

M.Sc. Research Project
Data Analytics

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Programme:	Master of Science-Data Analytics
Year:	2019
Module:	M.Sc. Research Project
Supervisor:	Vladimir Milosavljevic
Submission Due Date:	12/12/2019
Project Title:	Macroeconomic Forecasting of French Economy using Machine Learning Approach
Word Count:	XXX
Page Count:	23

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Abstract

Prediction of macroeconomic indices plays a crucial role for government agencies and economic entities because it helps them in framing the future fiscal policies and viewing the future outlook of a particular economy. This is the objective of this research where it finds the possibility of forecasting of unemployment and inflation for French economy using machine learning approach. The research employs Long Short-Term Memory network model for forecasting these indices and acceptable results are obtained which shows their usefulness. The performance of LSTM is comparable to baseline model of statistical approach by Vector Autoregressive. Also, the statistical model is used to comment on the validity of Phillips Curve in context with the French economy. It is found that there is a frail relationship between indices of unemployment and inflation but it is feeble enough to influence each other.
Keywords - Forecasting, Macroeconomic, unemployment, inflation, French economy, LSTM, Vector Autoregressive, statistical approach, Phillips Curve

1 Introduction

Macroeconomics is related to the analysis of a nation's aggregated economic status. This analysis is done on the basis of macroeconomic variables or indices, namely labour market indicators, inflation, gross domestic product, financial indicators and other related factors. Therefore, it is imperative to have a clear image of economic indicator at present and future times for its proper operation. The future values of indices are necessary for government agencies and financial entities of a nation for estimating its economic outlook. Forecasted values are also imperative for framing the fiscal policies of the economy. This creates the need for macroeconomic forecasting.

Classical forecasting models depend on using a defined relationship between variables, based on the hypothesis of a stochastic process. Analysis on Organization for Economic Cooperation and Development (OECD) statistics by (Turner; 2016) concludes for an assumption that the macroeconomic forecast is an equilibrium between model-based and judgment based. (Hall; 2018) gives an explanation that statistical modeling depends on mathematical concepts, resulting in less bias and subsisting forecasts. On the contrary, the consensus predictions depend on choice of models by the forecasters. Adding to these arguments, the machine learning approach for macroeconomic forecasting has been evaluated by (Ahmed et al.; 2010), (Coulombe et al.; 2019) and (Xu et al.; 2008), which makes it interesting to evaluate the predictive ability of machine learning models with statistical models.

The choice of French Economy, as a subject for this research, is based on multiple factors. It is the second largest contributor economy to GDP of European Union [1] whose national currency is based on the Euro, after Germany. The fiscal overview of France is considered neutral during the time period of 1996 to 2018. At the same time, the German economy was in state of contracting (Guillaume et al.; 2019). Adding to that, the French economy depends majorly on domestic demand, in response to the big public sector. These arguments make it a reasonable candidate for applying statistical and machine learning model. The economic model under consideration for this research is the Phillips Curve, which depicts an inverse relationship between inflation rate and unemployment rate (Samuelson and Solow; 1960).

Previous works in the related field have implemented the machine learning approach to macroeconomic forecasting for few of the world's prominent economies like United States (Swanson and White; 1997) and Russia (Sukhanova et al.; 2006) All the works deal with either aspect of statistical model or machine learning models. The novel aspect of this paper is to evaluate the forecasting results of economic model and machine learning model with reference to unemployment rate and inflation rate of France. Adding to that, the paper would also try to evaluate the relevance of Phillips Curve in context of the French economy with the help of time series analysis. To the best of knowledge, the above stated approach has not been found in any other referenced works.

The paper is formulated as follows: Section 2 describes the related and previous works done in the subject of econometrics and macroeconomics which Is relevant for this proposition. It also discusses about the French economy, Philips Curve and their relevance for this paper. Section 3 describes the methodology of the project, giving details about the datasets and models being implemented. Section 4 lays out the implementation part of the project in detail, covering the aspects of environmental setup, preparation of data, exploratory data analysis and experimental design. The implemented models are further evaluated in Section 5. The results are then discussed in Section 6, and then conclusion and future work with respect to the subject, in section 7.

1.1 Research Question and Objective

The objective of this research project is: What is the possibility of better forecasting of Unemployment and Inflation for France by using Neural Network.

More specifically, the research project will focus on below given objectives:

- Forecasting of Unemployment Rate and Inflation Rate of France by using econometric method.
- Multi-step forecasting of the two series individually by using Neural Network model.
- Commenting on the validity of Phillips Curve on French economy with the help of evaluated results

[1] https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20180511-1

2 Related Work

2.1 Discussion of French Economy

The discussion paper of European Commission on European economy (Guillaume et al.; 2019) states that the balance of export markets and products has favored the growth model of Germany to profit from the post economic crisis recovery. But this blend has exposed it to the oscillations of cycle of global economy. On the contrary, the reliability of growth model has been majorly on domestic demand in France, owing to the large public sector. This has resulted in smoothing of economic cycle, but on the price of compelling tax burden and loss in cost competitiveness. In Germany, a legal minimum wage was introduced in 2015 while it is been practiced since 1950 in France. France has comparatively higher unemployment in youth, as compared to Germany. This can be referred to from Figure 3, Pg. 5 in Configuration Manual.

In France, the focus of policies in labour market for youth is on job creation, while the expenditure on training is more in Germany. In the beginning of 1990s, the development in unemployment rate in France was in parallel with that of Germany. In 2002, it decreased and fell below the rate in Germany, owing to the crisis in early 2000s in Germany. But the continuing moderation in wage and reforms in labour market has helped in the decline of German unemployment rate. On the contrary, the positive trend in French unemployment rate got reverted, owing to the financial crisis in 2008.

The income inequality will remain higher in Germany, even if its unemployment rate fell significantly as compared to that of French. On average, the fiscal viewpoint of France can be considered to be neutral during the period of 1996 to 2018 while it was contractionary for the German economy in the same reference period. Owing to its less dependency on foreign trade and durable private consumption rates, the French economy sustained the financial and economic crisis comparably efficiently, as compared to other global economies. But the economic recovery, after the crisis period, has been relatively slow.

2.2 Phillips Curve and its relevance

In 1926, (Fisher; 1973) performed an analysis on economic data of United States and found relationship between unemployment rate and price levels. Similarly, a research by (Phillips; 1958) in 1958 analysed the data related to unemployment rate and money wages in United Kingdom between 1861 and 1957. As a result, it was found that there is an inverse relationship between the two economic indicators. The curve between unemployment and percentage rate of change of money wage rates per year shows an inverse relationship. The point where the curve crosses the X-axis (approx. 5.5) is the value of unemployment rate that an economy will observe at no or zero increase in wage rates.

A later research by Paul and Robert (Samuelson and Solow; 1960) used inflation, instead of rate of change of wages for the economy of United States and produced a similar result, coining it as 'Modified Phillips Curve for U.S.' as per the Figure 1.

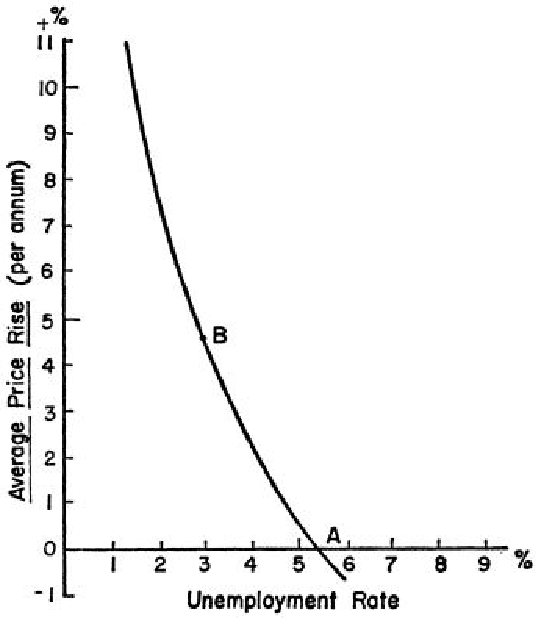

Figure 1: Modified Phillips Curve (Samuelson and Solow; 1960)

The analysis by (Berson et al.; 2018) focuses on the trend in the relationship provided by Phillips Curve on global economies by estimating it on the subject of G7 countries during the period of mid-1980 to 2016. The term G7 Is used to define a group of seven countries having the largest and advanced economies in the world. Current members of G7 are Canada, France, Germany, Italy, Japan, United Kingdom and United States. Since France is a member of the G7, therefore the above discussion is of interest with respect to the area of undertaken analysis of this paper.

It has been observed by (Blanchard; 2018) that there has been a symbolic decrease in the slope of Phillips Curve during 1980 to mid-1990 and since then, has remained stable around 0.5. Coefficient of inflation maintained a value less than 1 during the mid-1990s and then began to descend to limit around the value of zero during the current times. Therefore, it can be said that there has been a shift from influence of unemployment rate over variations in inflation. The curves for the same can be referred from the Configuration Manual, Figure 4 & 5, Pg. 6. This shift has been explained by (Blanchard; 2018) that the process of expecting inflation has changed from backward-looking to forward-looking, due to improvements in monetary policies. Adding to that, inflation could no longer play a role in estimating the wages, due to its low and balanced value.

2.3 Econometrics and Macroeconomics

(Committee; 2003) outlines the study of Economics Laureate Trygve Haavelmo, which has made it imperative to consider economic time series as an understanding of stochastic process. If this consideration is taken into account, then the statistical inference related with stationary process was left invalid. The study by Granger provided a solution to this issue by stating that models evaluating non-stationary, stochastic macroeconomic variables can be made such that their results are statistically and economically correct. He gave this observation by means of introducing cointegrated variables. In his research

(Granger and Newbold; 1974), he also stated that test of a regression, based on non-stationary variables may suggest relation between them but in reality, no such relation actually exists. Much of these relations may be spurious.

An approach by (Stock and Watson; 2017) investigates new development in the field of empirical macroeconomics by using external sources of randomness to find out the causal effects of shocks in macroeconomic variables. The approach to find these dynamic effects has been adapted from the branch of microeconomics, which already implements this approach to find the causal effects. The study employs two methods: One-step variable regression and two-step method which uses evaluation of vector autoregression. Both of these methods are applied on the same instrument. In terms of restrictive condition, the one-step method is accurate. Vector Autoregression is non- invertible, therefore a comparison of both the methods provides a measure for invertibility. In terms of less restrictive conditions, the validity rules for both the methods are similar. The control variables are endogenous variables which are lagged. These endogenous variables are evaluated by using the models.

A reference to econometric models can be drawn from the study by (Sukhanova et al.; 2016) which focuses on forecasting of macroeconomic factors for Russian economy using econometric models. The research is based on the Short Term Economic Indicators of Russian Economy. The economic variables under consideration were net export, consumer price index, unemployment rate, average monthly salary and other related indices. The results from the research indicated that ARIMA and VAR models show better forecasting results than SES type models on the basis of forecast errors. But the SES model had an advantage of evaluating relationship between endogenous and exogenous variables. Recent advancement in the field of economic forecasting also deals with the question of selection of indices for forecasting. (Stock and Watson; 2002) makes a point for the process of variable selection for forecasting methods. Currently employed methods for macroeconomic forecasting use less than 10 variables.(Stock and Watson; 2002) explain that although a small number of predictors are chosen from a set of variables, the forecasting performance of employed methods rely on limited number of chosen variables.

2.4 Machine Learning approach towards forecasting

A paper by (Xu et al.; 2011) introduces a data mining approach for forecasting the unemployment rate using web information in form of search engine query data. Selection of neural network in its optimum learning environment and architecture shows acceptable results by using the appropriate feature subset of the web information. The GA-NN-oss model exhibit comparable results, out of the different neural network models. Based on this research, the author puts forward an alternative idea for forecasting of unemployment rate.

There have been various arguments on the effective role of monetary policy on a country's economy. (Friedman; 1968) asserted that the effect of monetary policy on real economy could be decisive. On the contrary, researches by (Cover; 1992), (Morgan; 1993) and (Rhee and Rich; 1995) gave empirical results of lower impact on output growth through expansive monetary policy for United States. Therefore, it can be put forth that economic variable models of output growth may have non-linearities(Tkacz and Hu; 1999). On the other hand, models based on Neural Networks perform better in forecasting, as compared to linear models. There are numerous evidences in this regard by means of studies conducted between 1985 and 1998. One of the notable studies is by (Kohzadi et al.; 1995) which shows that the forecast error is marginally less than that of ARIMA model.

Multiple work has been done related to implementation of machine learning methods to forecast macroeconomic variables. A research by (Olivier and Angela; 2010) uses Joint Harmonized EU Business and Consumer Surveys, which covers sectors like services, retail trade, consumers, construction and manufacturing. The dependent variable is the quarter-on-quarter Euro Area GDP growth which is to be predicted based on the data provided by the survey. The approach for forecasting uses a combination of non-parametric random forest. Linear model provides better performance than auto-regressive model. It provides considerable results when compared to Euro Zone Economic Outlook and fast in response to real time survey data. A significant example of application of neural network for forecasting can be drawn from the work of (Xu et al.; 2008) which took indicator data from the reference period of 1978 to 2006 for economics and sampled it using Artificial Neural Network. The approach involved two models: Model one was trained by historical economic data and model two adapted the property of variation and delay in time series to describe the non-linear relation among various economic variables. By training the models on dataset enlarged by using chain-style data recombination method, a significant improvement in forecasting ability for both the model is observed. Based on the statement of (Stock and Watson; 2003) that time series of aggregate macroeconomic indices produces better forecasting as compared to individual series, (Liao; 2017) makes an attempt on data of 11 time series like unemployment rate, working hours per week, federal fund rate and try to use machine learning models for their forecasts. The results indicate that the performance of K-means Markov model for forecasting is in accordance with the values given by Survey of Professional Forecasters from Federal Reserve Bank of Philadelphia.

3 Methodology

In order to implement the research project, the model for CRISP-DM (Shearer; 2000) is taken as reference model for methodology.

Given below is a representation of the six phases of Research Project and the relationship between them, based on the CRISP-DM methodology.

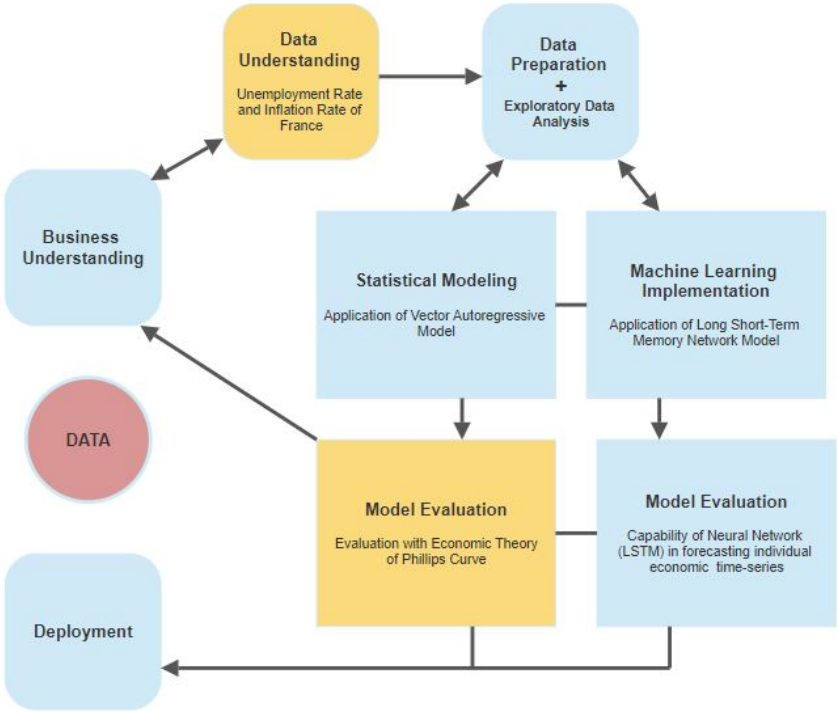

Figure 2: Process Flow Diagram for Research Project based on CRISP-DM model

3.1 Business Understanding

This initial phase concentrate on understanding of objectives of business perspective for which the solution needs to be developed. This information is further defined and a work-plan is devised to meet the stated objectives. The importance of economic forecast is very crucial for any particular economy. When there is a possibility of prediction of economic indices, it fuels certainty and confidence in economy. In order to adjust monetary policies, government entities and central banks require the procedure to draw forecasts of variables. This helps in smooth functioning of economy and helps then oversee any upcoming economic issues, to some extent. But the global environment compasses the component of uncertainty which hinders the predictability and leads to failure of forecasts. Despite of this, the practice of forecasting cannot be forsaken. The main objective of this research is to determine the relation between unemployment and inflation for French economy, in reference to the Phillips Curve and figure out the usability of machine learning for forecasting of unemployment and inflation.

The choice of France, as an economy, for this research, has been driven by many factors. Firstly, as per the information from Eurostat[2], France is the third largest economy in terms of its percentage share in total Gross Domestic Product of European Union in 2017, after Germany and United Kingdom. The selection criteria narrows down to Germany and France, on the basis of their adoption of common currency of the Euro.

[2]https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20180511-1

A comprehensive comparison of economies of Germany and France in the RELATED WORK section on their labor markets and fiscal policies indicate the French economy as a suitable option as it has less external influencing factors on its economy as compared to Germany.

3.2 Understanding of Data

The phase of data collection and understanding integrates the process of assembling data from credible and useful sources, describing data, and analyzing the integrity of data. The data for this research involves economic time series of macroeconomic indices such as unemployment and inflation. Given below is the detailed description of the different time-series used:

Unemployment of France : Standardized, including all ages and gender (male and female). The time series is percentage of civilian workforce which is adjusted for seasons and non-working days. The time series for Monthly Unemployment has been extracted from Statistical Data Warehouse-European Central Bank for 36 years, starting from January 1983 to December 2018.

Inflation or Harmonized index of consumer prices of France : Harmonised Index of Consumer Prices (HICP) measures the consumer price inflation in the Euro Area. 'Harmonised' term refers to the implementation of this methodology for measuring inflation index across the European Union. This index has been taken into account as France is a part of Euro Area. This is an overall monthly index which is not adjusted on the basis of seasons and working days. The monthly data of Inflation has been extracted from Statistical Data Warehouse-European Central Bank for 23 years, starting from January 1996 to December 2018.

For the ease of understanding and to avoid any confusion, the HICP measure is referred to as Inflation in the entire report.

Ethical Aspect of Data: The data is downloaded from the website of European Central Bank - Statistical Datawarehouse, which is a government agency and the data is freely available for public use without restrictions.

3.3 Data Preparation

This phase of CRISP-DM involves the action of processing the raw dataset into a final construct which can be further used for the modeling phase. The data preparation for the two time series has been explained as follows: The time series for unemployment and inflation is sourced from the European Central Bank website as a CSV file. The choice of CSV format is made for the convenience in processing and capturing all the relevant columns of the dataset. The raw CSV file contains information in terms of 34 columns.

Few of the notable parameters are: Serial key of the time series, Frequency, Reference Area, Adjustment Type, Time period, observed value and other columns depicting the properties of the time series. As per the research objective, properties such as monthly frequency, reference area of France and seasonally adjusted have been decided and are same for both of the time series under consideration, therefore they are omitted and final time series is retained in terms of their observed value of economic indices and the reference time period. The omission is made on the basis of the fact that the removed columns only serve the purpose of providing metadata of the time series and play no active role for the analysis and modeling section. The reference time period for each of the time series has been decided on the basis of their applicability on the various models, which has been put forward in the next stage of methodology.

3.4 Modelling

The phase of modeling enumerates the model that would be applied to the reference data, which can provide an effective solution to the objectives. It specifies the best choice of model to be applied on the data prepared in the data preparation phase. In this study, statistical analysis is conducted on the two time series using Vector Autoregression (VAR) and then the machine learning approach for forecasting of unemployment and inflation will be implemented by using Long short Term Memory (LSTM).

- **Vector Autoregression :** A paper by (Sims; 1980) has substantiated VAR or Vector Autoregressive models as a standard approach in econometrics for conducting analysis in terms of multivariate dataset. VAR models are apt in explaining the endogenous variables by means of their own history besides the effect of regressors which have a deterministic effect. Regressors are the independent variables in the regression equation while the endogenous variable is a variable which is influenced or determined by other variables in the statistical model, on the basis of their relationships. As compared to uni-variate or AR models, the adoption of VAR approach for economic analysis and forecasting has been supported by studies of (Ramos; 2003) and (Gooijer and Hyndman; 2006).

- **Long Short-Term Memory :** Long Short-Term Memory (LSTM) is a category of Recurrent Neural Network which has the potential to remember values from previous phases so that it can be made to use for future needs. RNN or Recurrent Neural Network is a class of Neural Network which aims to forecast next steps with respect to the previous steps, in a sequence. It uses observations from the sequence to learn so that future trends can be forecasted. They are known as 'recurrent' as their hidden layers operate as storage to store information of previous stages of sequence and perform similar task for each element of sequence. Studies by (Gers et al.; 2000) and (Hochreiter and Schmidhuber; 1997) have shown the application of LSTM in time series prediction. LSTM is a certain class of RNN which memorizes the data sequence. Each LSTM is a collection of modules where the stream of sequence is stored. Owing to the gates in each module or cell, data in each of them could be filtered or combined for next cells. Therefore, gates based on layer of sigmoidal neural network, i.e. Forget Gate, Memory Gate and Output Gate allows the choice of passing or disposing data to the cells.

  LSTM for forecasting, is based on rolling forecasting origin (Hyndman and Athanasopoulos; 2018). It is required for this research because the time series is dependent on its previous values. The methodology of this research focuses on monthly forecasts, therefore it concentrates on the next forecast for each dataset and uses train data which contains one-month look ahead observation of the data. Rolling forecast is also referred as walk-forward model validation.

3.5 Evaluation

The evaluation phase of the methodology deals with examining the developed model to find its usability in solving the stated problem and objectives.

The metric for assessment and evaluation of both the developed models will be Root-Mean-Square Error or RMSE. It is a measure used for estimating the accuracy of prediction given by the model in terms of the difference between actual and predicted values.

Equation (1) represents the formula for computing RMSE (Barnston; 1992):

$$RMSE_{fo} = \sqrt{\sum_{i=1}^{N} (z_{fi} - z_{oi})^2 / N} \tag{1}$$

where Z_{fi} and Z_{oi} represent the values for forcasted and observed values and N is the sample size.

In addition to the evaluation metrics, the performance of LSTM would be evaluated against the persistence model which is based on the persistence algorithm. The persistence algorithm adopts the previous time step (t-1) value of time series to predict the value at next time step (t+1) (Brownlee; 2017). Therefore, this naïve forecast could be used as a baseline model for evaluating the performance of LSTM forecasting model.

3.6 Deployment

The final stage of the methodology is the deployment of final evaluated model to provide solution of the stated problem and objectives. The detailed report of the research would be an attempt to provide an extensive description of the applied models and it would be useful for reproducibility of the solution on other related objectives and for further improvements on the implemented solution, if any.

4 Implementation

This phase gives a detailed description of the various steps of implementing the Vector Autoregressive and LSTM on the time series of Unemployment and Inflation. The different stage of implementation consists of Environmental Setup, Data Preparation and Experimental Design. These are explained as follows:

4.1 Environmental Setup

Vector Autoregression on the two time series is implemented in R v3.5.2 while the implementation of LSTM is performed in Python v3.7.4. The model implementation for Vector Autoregression employs statistical packages present within R while the LSTM implementation makes use of Keras with TensorFlow background. The advantages of using Keras is that it is easy in implementation and comprehension and due to its support for the neural networks (Gulli and Pal; 2017).

4.2 Data Preparation

- **Vector Autoregressive Model :** The CSV files of unemployment and inflation are read into two separate dataframes. The inflation is available for 23 years on monthly basis while the unemployment is present for 36 years on monthly basis. In order to evaluate both the time series on the same scale, the unemployment series is trimmed so that both of the series are from January 1996 to December 2018. These two dataframes are then converted to time-series (ts) objects. Conversion into time-series (ts) objects is necessary because it makes the objects suitable for time series analysis (Hyndman and Athanasopoulos; 2018).

  NOTE : For the ease of understanding, the time-series objects for unemployment is referred as UNRATE and for inflation, it is referred as HICP. Both the objects are referred as the same abbreviated names in the remaining report.

  For the purpose of processing the data into model, the combined object of two series are split into train and test with a split ratio of 70:30. Therefore, the test set contains object values from January 1996 to December 2011 while the test set contains values between January 2012 and December 2018.

- **Long Short-Term Memory :** The interest of the research is to evaluate multivariate forecasting capability of LSTM for each of the two time series, unemployment and inflation. In supervised learning, an algorithm is used to gain information about the underlying function for the mapping of input variable to output variable of the referred data. Therefore, by using the shift() function in Pandas, the columns which needs to be pushed forward or backward can be manipulated. This is useful for creating lagged observations and forecast observations of data as a supervised learning format.

  The next step is the creation of differenced series. The statistical analysis of both time series of Unemployment and Inflation while applying the VAR model indicated that the raw series are non-stationary. So, differencing the time-series converted it to a stationary series, which was proved by the results of Augmented Dickey Fuller test on the differenced series. Therefore, for the purpose of forecasting using LSTM, the time series is converted as a first order differenced series to make it favorable for modeling.

  Before splitting the time series into train and test set, the time series required scaling of data. Scaling is performed in order to maintain the variance of features in the same range. In absence of scaling, one of the features may have more variance as compared to others which may affect the functioning of forecasting model. Although there is a single feature in each time series but scaling has been performed in order to limit the variance of data between the specified range and ascertain the validity of model's output. The data is split into train and test set. The train set is used to train the LSTM model and its performance is tested by evaluating its forecast with the test set.

4.3 Exploratory Data Analysis

Graphs are plotted for both the objects of UNRATE (Unemployment) and HICP (Inflation) to check for any seasonal trends in the time series. Referring to figures 8, 9, 10 and 11 in Configuration Manual, Pg. 9-10, the object values are plotted against the 12-month period for all the years in the object. This graph indicates absence of any seasonal components in the object values as the unemployment remains same for the years, irrespective of the seasons. The overlapped values of few years indicate that the indicator value for these years is almost same.

4.4 Experimental Design

4.4.1 Vector Autoregressive (VAR)

- **Optimal Lag Length Selection** : Both the UNRATE (Unemployment) and HICP (Inflation) objects are combined to form a single object and optimal lag length is calculated for the single object.

  Referring from the output of lag length selection from figure 12, Pg. 11 in Configuration Manual, lag length is selected as 2 because it has the minimum value for the information criteria. Selection of optimal lag length, delay or previous values of time series, is a crucial step in time series analysis because large number of lags may boost the standard errors of coefficient estimates and can increase the forecast errors while neglecting useful lags may lead to bias in estimation. The order or lag length has been decided on the basis of Information Criteria (Dziak et al.; 2012) like AIC (Akaike Information Criteria) and HQ (Hannan-Quinn Information Criteria). HQ Is an alternative for AIC and BIC (Bayesian Information Criteria).

- **Check for Stationarity** : To check for the property of stationarity, Augmented Dickey Fuller or ADF test (Dickey and Fuller; 1981) is conducted on the individual time series. The ADF test is an examination for unit roots in time series. Unit roots are cause of non-stationarity. A time series is deemed to be stationary if a single shift in the referenced time does not affects the statistical properties of time-series which confirms the non-existence of unit roots.
  ADF test on UNRATE object (Figure 13, Page 12, Configuration Manual) gives the p-value as 0.2641 which is greater than the significance level of 5% or 0.005. ADF test on HICP object (Figure 13, Page 12, Configuration Manual) gives the p-value of 0.6085 which is greater than significance level of 0.005. The null hypothesis of ADF test states that there is presence of a unit root and the alternate hypothesis denies the presence of unit root. The p-values for both the UNRATE and HICP objects confirms the presence of unit roots. Therefore, first order differencing is performed on both objects and then, subjected to a re-run of ADF test.
  p-value for ADF test on differenced UNRATE gives p-value of 0.03789, which is less than the significance level of 0.05 (Figure 14, Pg. 13, Configuration Manual). Similarly, the p-value of ADF test on differenced HICP gives p-value less than 0.01 which is smaller than 0.05 significance level (Figure 14, Pg. 13, Configuration Manual). This confirms that both the objects are now converted into stationary series.

Therefore, a plot is drawn for both the series objects which shows the objects to be stationary. This can be referred from Figure 15,16: Pg. 14 in configuration Manual. Since both the objects are now first order differenced, therefore they are combined to form a single object and lag length is selected for this object. As per the minimum values of information criteria, the lag length is 1.

- **Check for Cointegration** : Test for cointegration evaluates the correlation between non-stationary variables of time series type. If two time series are non-stationary in individual nature, but a linear combination of both of them comes out to be stationary, then both the series are termed as cointegrated series. Johansen-Cointegration test is a method to test such a relationship between two or more time series variables (Johansen; n.d.). Johansen-Cointegration test on combined undifferenced series objects of UNRATE and HICP gives the following results, which can be referred from test output in Figure 18, Pg. 15, Configuration Manual :
First hypothesis, r=0 states that test statistics of 21.08 is less than 25.32, which is the value at 5% significance level. This indicates no cointegration between the two time series objects. The second hypothesis, r¡=1 indicates that test statistics of 6.50 is less than 12.25, value at 5% significance level. This also indicates towards the absence of cointegration.

- **Check for Causality** : The concept of Granger's non-causality test (Granger and Newbold; 1974) deals with the construct of prediction of a given variable x from the past values of itself and another variable y. This can also be stated as x is Granger-caused by y, as the preceding values of variable y could be useful in predicting variable x in a more precise manner, as compared to only using the past values of x. It can also be affirmed that Granger causality deals more with prediction, as compared to causation in general terms. A point worth considering is that evaluating causality test on non-stationary data can give spurious results (Park and Phillips; 1989), (Sims et al.; 1990) and (Stock and Watson; 1989) . Therefore, causality test is performed on differenced UNRATE and HICP object and the output of these tests can be referred from Figure 19,20; Pg. 16, Configuration Manual.
The output of test on relation (HICP causes UNRATE) accepts the alternate hypothesis that lagged values of unemployment cannot explain the variation in inflation because value of Pr(>F) = 0.3252 is greater than 0.05, value at 95% confidence interval. The test result on relation (UNRATE causes HICP) rejects the null hypothesis because Pr(>F) = 0.6634 is greater than 0.05, value at 95% confidence interval. Therefore, the lagged values of inflation cannot explain the variation in unemployment.

In case of two variables, when both the series are found to be I(1) or first order differentiated and have no cointegration, then the best possible model for implementation is the Vector Autoregressive, in terms of their first differencing (Iorio and Triacca; 2013).

4.4.2 Long Short-Term Memory (LSTM)

Once the data has been processed for first order differencing and split into train and test set, the next step is to fit a LSTM model to the train set for both the time series. In an attempt to reduce the complexity of model, a simple network is considered with the

following specifications:
one hidden layer, one LSTM unit, one output layer having linear activation function with three output values. Hidden layer is one of the three layers of input, hidden and output layer. The function of hidden layer is to transform inputs into a state which is usable by the output layer. Linear activation function at the output layer is a straight line function in which the activation is proportional to the input. The weighted sum of inputs is calculated by neurons, bias is added and value is feeded to activation function which makes the output.
The loss function for the network is mean squared error while the optimization used is Adam. Adam (Kingma and Ba; 2015) combines the ability of AdaGrad, to deal with sparse gradients, and RMSProp for non-stationarity. After the training data is fit to LSTM network, the model is used to make forecasts for the two time series, separately. Once the forecasting has been done, it is required to invert the transforms so as to scale the values to their original dimensions. This step is crucial in order to calculate the evaluations metrics of root mean square error.

5 Evaluation and Result

5.1 Vector Autoregressive (VAR) model

The model is evaluated in terms of Root Mean-Square Error. Below are the values for two time-series objects:

Time Series Object	**ME**	**RMSE**
unrate_diff test set	0.0526	0.0701
hicp_diff test set	0.0145	0.4391

Table 1: Evaluation metrics for Vector Autoregressive Model

Where 'unrate_diff' is the unemployment in terms of first difference and 'hicp_diff' is the inflation in terms of first difference.

Once the VAR model is implemented, it is evaluated for impulse response. The impulse response function analyses the dynamic effect of whole system in response to an impulse. Response of unemployment 'unrate_diff' for impulse of inflation 'hicp_diff', as given in figure 3, indicates that there is a slight positive response around 2^{nd} time period and starts decreasing to its absence, with increase in time period.

On the other hand, response of inflation due to impulse of unemployment, as shown in figure 4, depicts that the response is negative at the 2^{nd} time period, goes on decreasing with the time period and gradually dies.

The VAR model is finally tested for serial correlation. Serial correlation is a relationship between error term between two time intervals, in a time series. The presence of serial correlation in a model violates the assumptions in original model and then a relationship has to found between the error terms.

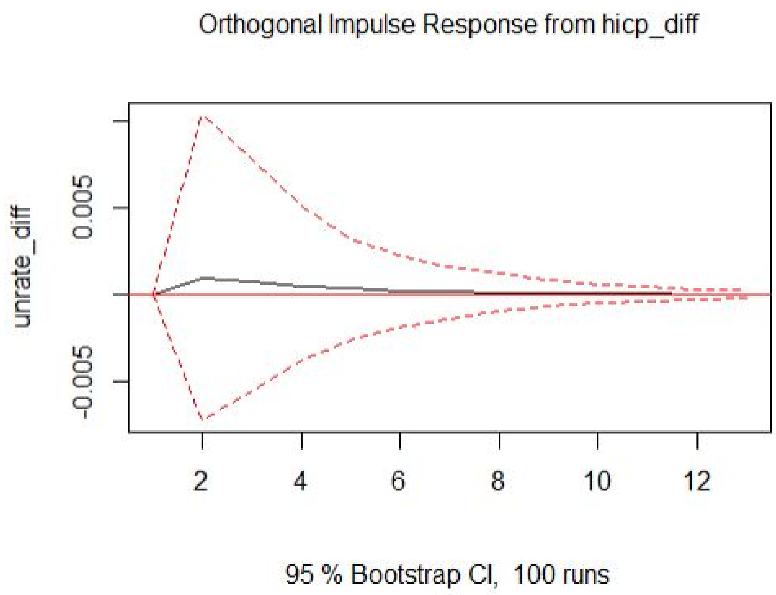

Figure 3: Response of Unemployment on impulse of Inflation

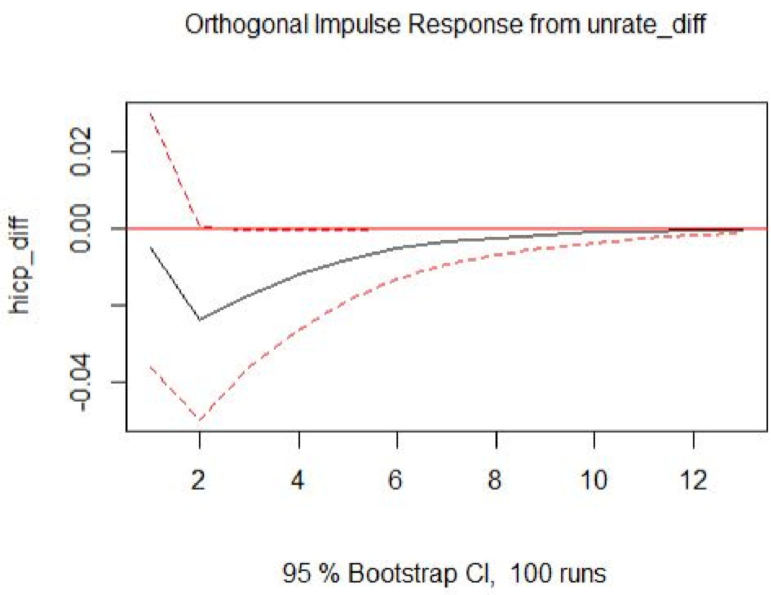

Figure 4: Response of Inflation on impulse of Unemployment

Portmanteau Test (asymptotic)	
data	Residuals of VAR object model_var_d
chi-squared	7.3128
df	8
p-value	0.5033

Table 2: Test result of Serial Correlation on VAR Model

The output of the test on VAR model indicates the p-value of 0.5033 which is greater than the significance level of 0.05. This confirms the absence of auto-correlation in the estimated VAR model as we fail to reject the null hypothesis of no auto-correlation, based on the p-value.

5.2 LSTM Model

Once the LSTM model is fitted for forecasting, the evaluation of the model is performed by means of calculating the Root Mean-Square Error at each time-step of forecast.

Parameter Tuning: The fitted model is able to provide forecasts of both the time series separately but it is crucial to tune the parameters by means of iterations to find out the best fit model for the given configuration. This is performed by means of executing the model with different values of epoch and neurons. A single epoch processes the entire dataset through the LSTM network, for once. The gradient descent used is an iterative process, therefore to optimize the learning of our model on our limited dataset, multiple epochs needs to be provided.
For time series of unemployment, the value of RMSE for different epochs and neurons is tested and given in Table 3 & 4.

Epoch	**RMSE**
200	0.0775
400	0.0758
600	0.0893
800	0.0896
1000	0.0796

Table 3: RMSE values for different epochs

Neurons	**RMSE**
1	0.0758
2	0.0764
3	0.0746
4	0.0786

Table 4: RMSE values for different neurons

The minimum RMSE value is obtained for 3 neurons and 400 epochs. Therefore, the parameters for optimum performance of model, in the given case will be 3 neurons and 400 epochs.

Similarly, for the time series of inflation, RMSE values for different epochs and neurons is evaluated and minimum value of RMSE is obtained for 600 epochs and 1 neuron.

Epoch	**RMSE**
200	0.4255
400	0.4073
600	0.3988
800	0.4263
1000	0.4255

Table 5: RMSE values for different epochs

Neurons	**RMSE**
1	0.3988
2	0.4194
3	0.4161
4	0.4185

Table 6: RMSE values for different neurons

Therefore, the parameters for optimum performance of model for multi-step prediction of inflation will be 600 epochs and 1 neuron. The performance of model is evaluated on below methods of data split:

Sequential Split Since the data is time series and the functioning of LSTM is dependent on data sequence, therefore the data is split sequentially. The split ratio taken here Is 70:30. For the time series of unemployment, train set includes values between January 1983 and December 2007 and test set includes values between the time periods of January 2008 and December 2018. Similarly, for the inflation, train set contains values from January 1996 to December 2011 while test set contains value from January 2012 to December 2018.

Cross Validation for time-series Apart from the normal data split to train and test, cross validation is used for time series. In this method, there is a series of single value test sets and the analogous train set contains values of time series which appear before the test set values, in terms of their appearance in the original time series (Hyndman; 2016). In this manner, no future values will be employed in forming the forecasts.

5.3 Main Findings

For the two series of Unemployment and Inflation for France, table 7 shows the RMSE values for forecasts by the Vector Regressive Model and table 8 and 9 depicts the multi-step forecast by the LSTM model. In case of LSTM model, multi-step refers to value of forecasts at t+1, t+2 and t+3 time steps.

Forecast Result by VAR model: Unemployment and Inflation

Time Series	RMSE
Unemployment	0.0701
Inflation	0.4391

Table 7: RMSE values for forecasting by VAR

Multi-Step Forecast Result by LSTM: Unemployment

Persistence Model	Sequential Split	Cross-Validation
0.0902	0.0771	0.0835
0.1606	0.1378	0.1438
0.2228	0.2001	0.2058

Table 8: RMSE values for multi-step forecasting by LSTM

In case of LSTM implementation for unemployment, the sequential split gives lower RMSE values, as compared to persistence model and cross-validation of time series.

Multi-Step Forecast Result by LSTM: Inflation

Persistence Model	Sequential Split	Cross-Validation
0.4207	0.4138	0.3887
0.5297	0.5078	0.4922
0.6295	0.5840	0.5778

Table 9: RMSE values for multi-step forecasting by LSTM

While in case of LSTM forecasts for inflation, satisfactory and lower RMSE values are obtained by cross-validation method.

6 Discussion

This research project gives an insight about the application of neural network in forecasting the macroeconomic indices of unemployment and inflation in case of France. It also evaluates the performance of machine learning model with the standard economic approach. Forecasting of these economic indices is useful because it gives a future outlook of the economy for better planning. It also helps the government agencies and central banks in designing their fiscal policies for the coming time periods.

The datasets for this research are Unemployment and Inflation of France. Unemployment is taken for 36 years, from 1983 to 2018 on monthly basis. Inflation is taken for 23 years, from 1996 to 2018. Exploratory data analysis on the two dataset confirms the absence of seasonality in both the series. The research project is implemented using the CRISP-DM methodology.

The statistical approach to forecasting is implemented in reference to economic model of Phillips Curve, using Vector Autoregressive Model. The combined series of unemployment and inflation is taken and converted to time-series objects. The stationarity test shows that both the series convert to stationary entities after first differencing. The research also shows that the non-stationary variant of both the series are not correlated, leading to absence of cointegration. The statistical analysis also confirms that inflation does not causes unemployment and vice versa. The test for serial correlation on the model indicates that there is no relationship between the error terms in terms of two time intervals.

In terms of machine learning approach, a simple network of Long short-Term Memory is applied separately on the two series to find out their forecasts. Individual forecasts is performed because of absence of cointegration and causality between the two series. Adding to that, LSTM network works on previous sequences and is one of the best choices for univariate forecasting.

On the basis of evaluation metric of RMSE, the statistical approach of VAR model gives RMSE of 0.0701 for unemployment and 0.4391 for inflation. On the other hand, the multi-step forecast of unemployment by using LSTM gives RMSE of 0.0771, 0.1378 and 0.2001 while the error values are 0.3887, 0.4922 and 0.5778 for inflation. The results of LSTM model are comparable and satisfactory, with reference to the baseline model of persistence and statistical method.

The impulse response analysis of VAR model is in slight disagreement with the causality test by showing that there is a slight positive response in unemployment with respect to impulse from inflation. Negative response from inflation is recorded, due to an impulse by unemployment.

7 Conclusion and Future Work

The research project addresses the possibility of implementation of neural networks for time-series forecasting of economic indices. The scope of research includes the time series for Unemployment and Inflation of France and attempts to forecast them using Long Short-Term Memory network model. The experimental setup gives comparable and acceptable forecasting results with reference to the baseline models of persistence and econometric approach of Vector Autoregressive Model. Therefore, it can be asserted that neural networks or machine learning approach can be useful for macroeconomic forecasting.

About the validity and application of Phillips Curve in French economy, in terms of this research, it can be remarked on the basis of statistical analysis that there is no correlation between the two economic series. Also, the test of causality shows that unemployment does not causes inflation and vice versa, in case of French economy between the period of 1996 and 2018. The error terms also shows no correlation. Therefore, on the basis of this research, it can be said that values of these two time series are independent of each other. Adding to that, the impulse response analysis of the Vector Autoregressive Model indicates a positive response of unemployment due to inflation impulse and inflation shows a negative shock in response to unemployment impulse. This indicates a relationship between these two indices for French economy but it is weak enough to influence each other.

8 Acknowledgement

As part of the efforts towards this research project, I extend my acknowledgment to my supervisor, Professor Vladimir Milosavljevic for his perpetual support and encouragement which assisted me in successful completion of this project. I would also extend my gratitude to my parents and friends for their eternal support.

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