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Quantum Neural Networks for Forecasting Inflation Dynamics

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Inflation is a key indicator in the economy that measures the average level of prices of goods and services, being an important ratio in public and private decision-making, so predicting it with precision has always been a concern of economists. This paper makes inflation predictions with different time horizons applying quantum theory through Quantum Neural Networks. The results obtained teach that Quantum Neural Networks overcome the predictive power of the existing models in the previous literature and yields a low-level of errors when predicting any change in the direction of the forecast trend.

Keywords: Inflation dynamics, Neural Networks, Quantum Computing, Quantum Neural Networks, Macroeconomic forecasting

Introduction

Predicting the inflation rate of the economy with great precision has always been one of the economists' concerns. This enormous interest in predicting this indicator comes from its nature as a key index in decisions in macroeconomic policy by public institutions, such as the decision-making of legal interest rates of central banks, but also of private institutions such as financial, since they must take into account inflation to calculate the expected real profitability of the market, among other concerns. Empirical studies that focus on the construction of inflation prediction models have used different methodologies and approaches for post-estimations. Ulke, Sahin, and Subasi[1] determined that the autoregressive distributed lag model methodology obtained the lowest root mean squared error (RMSE) with a value of 0.62 for a horizon of 6 months, while support vector machines was shown as the most accurate methodology for a longer horizon (12 months) with an RMSE of 1.66. Acosta[2] applied the algorithm k-means to predict inflation in Mexico obtaining an RMSE of 0.20. Duncan and Martínez-García[3] applied the factor-augmented model obtaining 56% accuracy at the maximum horizon of one year with an RMSE of 0.751. Medeiros *et al*.[4] concluded that the Random Forests technique gave the lowest RMSE a value of 0.72 for a 12-month horizon. Finally, Hassani and Silva[5] applied the Multivariate Singular Spectrum Analysis (MSSA) achieving a RMSE of 0.337 for a 36-month horizon. Although the advances in inflation prediction have been extensive in recent years, the literature demands greater precision regardless of the time horizon used. To respond to this need, this work proposes the Quantum Neural Network methodology, using a hybrid approach to quantum calculus combined with artificial multilayer neural networks, also called classical neural networks. The empirical results of the present study show a lower level of errors than previous studies in predicting inflation[1-4], using time horizons of 3, 6, 12, 24 and 36 months, in addition to taking into account changes in the direction in the trend in order to get a dynamic prediction.

Quantum Neural Networks (QNN)

Wan *et al*.[6] showed the possibilities of combining CNN's unique computational capabilities and quantum computing. This combination can create a computational technique with great predictive potential. The input layers of QNN are classic, the hidden layers are quantum neurons and the output layers are classic. The QNN is built from quantum computation techniques. Qubit is defined as the smallest unit of information in quantum computation which is a probabilistic representation. A qubit may either be in the “1” or “0” or in any superposition of the two[7,8]. The state of the qubit can be defined as follows:

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Table 1 — Results of accuracy evaluation

	Classification (%)		RMSE		Direction Changes (in RMSE terms)	
	Training	Testing	Training	Testing	Training	Testing
CPI-all						
h=3	99.49	98.45	0.08	0.13	0.12	0.14
h=6	98.74………..	97.82	0.12	0.15	0.16	0.17
h=12	98.18	97.06	0.16	0.19	0.19	0.21
h=24	97.57	96.11	0.18	0.22	0.24	0.27
h=36	96.24	94.76	0.21	0.24	0.29	0.33
CPI-core						
h=3	99.78	98.92	0.07	0.12	0.11	0.12
h=6	99.13	98.04	0.12	0.15	0.15	0.16
h=12	98.58	97.31	0.14	0.18	0.18	0.20
h=24	97.81	96.72	0.16	0.20	0.23	0.26
h=36	97.10	95.66	0.19	0.22	0.28	0.32

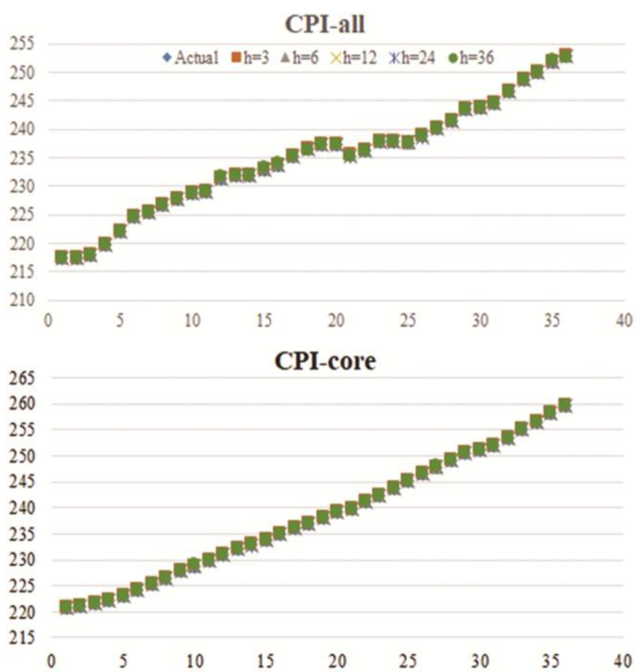

Fig. 1 — Results of accuracy evaluation

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad \ldots (1)$$

where α and are the numbers that point out the amplitude of the corresponding states such that $|\alpha|^2 + |\beta|^2 = 1$. A qubit is defined as smallest unit of information in quantum computation. It is determined as a pair of numbers$\begin{bmatrix}\alpha \\ \beta\end{bmatrix}$. Angleθis specification that represents geometrical aspects and is defined such that: cos(θ) = |α| and sin(θ) = |β|. Quantum gates may be applied for adjusting the probabilities as a result of weight upgrading[8,9]. An example of rotation gate can be:

$$U(\Delta\theta) = \begin{bmatrix} cos(\Delta\theta) & -sin(\Delta\theta) \\ sin(\Delta\theta) & cos(\Delta\theta) \end{bmatrix} \quad \ldots (2)$$

The next hybrid quantum inspired neural network is proposed for forecasting inflation dynamics. The process is begun with a quantum hidden neuron from the state$|0\rangle$, prepare the superposition:

$$\sqrt{p}|0\rangle + \sqrt{1-p}|1\rangle with\ 0 \le |p| \le 1 \quad \ldots (3)$$

where p represents random probability of initializing the system in the state $|0\rangle$.Previous works as Mahajan[8] are necessary to check more mathematical developments about quantum hidden neuron.

The classical neurons are initiated by random number generation[8,9,10]. The output from quantum neuron is determined as problem dependent sigmoid or Gaussian function[8].The learning follows the rules of feed forward back propagation algorithm. Upgrading of quantum hidden layer weight in quantum back propagation algorithm the weights are upgraded by quantum gate conforming to equation (3)[8], so in this case the equation would be:

$$\begin{bmatrix}\alpha_{ij}' \\ \beta_{ij}'\end{bmatrix} U(\Delta\theta) = \begin{bmatrix} cos(\Delta\theta) & -sin(\Delta\theta) \\ sin(\Delta\theta) & cos(\Delta\theta) \end{bmatrix} \begin{bmatrix}\alpha_{ij} \\ \beta_{ij}\end{bmatrix} \quad \ldots (4)$$

Where the learning rate (η) applied by previous works[8,11,12], using the value 0.1.

Direction of change criterion

We apply the change the direction criterion to predict the turning points for the forecasted series of inflation obtained by QNN. Direction of the change refers to the changes in the sign of the slope of the time series. It shows proportion of forecasts that correctly predicts direction of series movement. Let Z_t (t = T + 1, ..., T + n)takes a value of 1 if the predicted series correctly predicts the direction of the change and 0 otherwise. The central limit theorem of Moivre-Laplace[12]involves that for large samples the test statistic $2(Z – 0.5)n^{1/2}$is distributed approximately as standard normal. When $\overline{Z}$ is significantly greater than 0.5, the forecast is said to have the ability to forecastthe direction of the trend change. On the other hand, if $\overline{Z}$ is significantly less than 0.5, the forecast tends to give the wrong direction of change signal.

Results and Conclusions

We use several US price indices in out-of-sample, h-step-ahead moving prediction exercises. These indices include the CPI including all items (CPI-all) and the CPI without highly volatile food and energy items (CPI-core).We divide sample observations from 1985Q1 to 2009Q4 of the GDP price index for training sample and observations for 2010Q1–2018Q4for out-of-sample predictions (testing sample).

Table 1 reports on the accuracy and the direction of change obtained for h=3,6,12,24 and 36 months as different time horizons. These models have been developed using 2000 random data sets, to which 10-fold cross-validation was applied, randomly dividing and mutually exclusive, the available set of samples by 70% for training sample, and 30% for testing sample. The accuracy rates obtained with the training sample of CPI-all reach 99.49% for the horizon h=3, 98.74% for h=6, 98.18% for h=12, 97.54% for h=24 and 96.24% for h=36, while the training sample of CPI-core obtain 99.78% for h=3, 99.13% for h=6, 98.58% for h=12, 97.81% for h=24 and 97.10% for h=36. The accuracy rates obtained with the testing sample of CPI-all reach 98.45% for the horizon h=3, 97.82% for h=6, 97.06% for h=12, 96.11% for h=24 and 94.76% for h=36, while the testing sample of CPI-core obtain 98.92% for h=3, 98.04% for h=6, 97.31% for h=12, 96.72% for h=24 and 95.66% for h=36.Additionally, Table 1 presents training and testing results for the null hypothesis of whether the percentages of the directions of change are greater than pure chance (50%).With respect to the prediction results for the CPI-core series they are better than the prediction results obtained for the CPI-all series. Perhaps this could be due to the high volatility of food and energy prices, which are excluded in the construction of the CPI-core series. Similarly, the precision results of the present study improve those obtained in the previous literature[1-4]. The results in Table 1 also show that QNN predicts the direction of the change with a lower error level than those obtained in previous works[1-5], while these levels of errors obtained increase steadily as we increase the time horizon of prediction. The same pattern is maintained in which the direction of trend change is better predicted for the CPI-core series than for the CPI-all series. Figure 1 shows the testing forecast values for 3, 6, 12, 24 and 36 month horizons of the QNN model. These results improve the accuracy obtained both training and testing data by previous works[1-5]. Finally, it should be noted that the parameters used by the hybrid quantum model of neural networks with backward propagation are 40 quantum hidden neurons and 40 classical output neurons.

Inflation forecasting is a worldwide phenomenon that has been the focus of concern for researchers and public policy makers in the last decade. Our results show that Quantum Neural Networks improve the accuracy of existing inflation forecasting models, as well as showing the possible changes of trends in the different time horizons. Previously, they offer a greater amount of information for the policymakers considered that need empirical tools to predict as accurately as possible the most immediate inflation data. Also, our models can be of special relevance to government bodies and financial institutions, such as rating agencies and central banks, that need to control the next value of inflation and his trend. We leave for further research the question about whether QNN method can systematically outperform standard methods when other macroeconomic series and countries are considered.

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