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NEUROCOMPUTATIONAL ECONOMIC FORECASTING WITH A HANDFUL OF DATA

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Abstract

Economic forecasting is always difficult and in turbulent periods becomes nearly impossible: Time-series are short and nonstationary while theoretical underpinning is limited. The brain, however, has mechanisms to deal with that kind of challenges, and neuroscience has uncovered some of them. Here we show how a neural circuit model for emotion generation is adapted to successfully predict fluctuating macroeconomic indicators with only a handful of observations. A fractality principle, stating that brain cognitive processes project and repeat themselves on the time scale of socioeconomic processes, suggests why economic cycles resemble emotional neurodynamics.
Key words: machine learning, gated dipole, economic forecasting

Introduction. The brain has evolved to make decisions about the future in a changing environment, and neuroscience models have shown some success in emulating that property. The progress achieved so far could be transferable to other areas, for example economic and business forecasting. Economists calibrate predictive models based on assumptions about the underlying fundamentals. They face, however, a number of problems: their models lay on shaky theoretical ground, time-series are generally short, and unexpected events impact processes nonstationary anyway. Economies fall in and out of high volatility periods, undergo booms and busts, yet the onset and magnitude of a slump are largely unpredictable [1,2]. High-impact shocks like those triggering the recession of 2007–2009

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or the 2020 pandemic introduce regime shifts in businesses and entire economies, rendering historical data essentially useless. Lack of records is also the norm in a start-up or an established company launching a completely new product or service. All these issues make the conventional forecasting techniques inefficient when most needed, and novel approaches must step in.

Materials and methods. Here we show how a neural circuit model has the potential to substantially improve prediction in cases like the above. The main idea is based on a concept known as social or socioeconomic fractality, which connects mechanisms in neural and social networks [3]. It posits that brain cognitive processes in the sub-second range project and repeat themselves on the scale of months and years in the lives of groups, societies, and countries. Previous research suggested that as the brain evolved for hunting and social cohesion, elements of its structure projected over to social networks [4–6], while some neural interactions were found to resemble competitive markets [7,8].

Figure 1 illustrates our main point. In general, having a nonstationary process and only two observations, the usual statistical means may go wrong. To come closer to the truth, a model capturing a deeper insight about the system is needed and its prediction can go in an unusual direction. Its accuracy would depend on how adequate the adopted theory for the problem at hand is. In this paper,

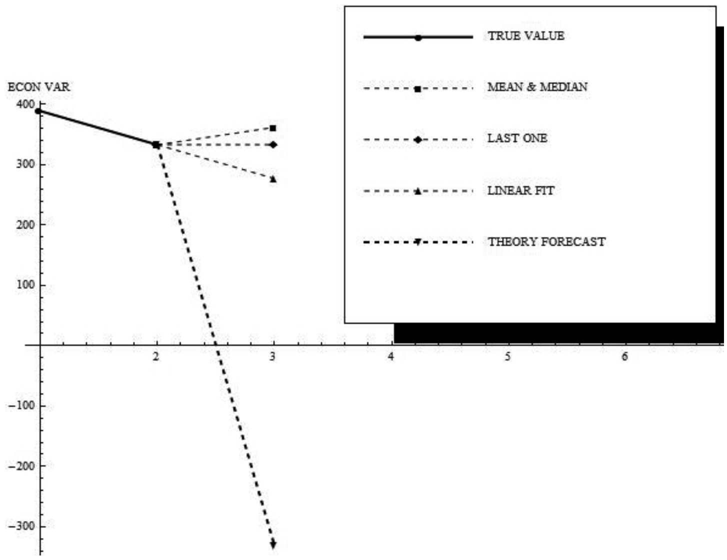


Fig. 1. Forecasting a variable based on only two observations: The mean, median, last value, or a line between the two points can go wrong with a nonstationary process. A deeper theory may suggest an entirely different prediction. The example "Theory Forecast" is a neurocomputational prediction of the macroeconomic variable investment (GFCF) in Montenegro in 2009 based on two previous years' data. (See text)

we emulate economic fluctuations with a neural circuit for affect generation and processing known as gated dipole [9]. It accounts for the loosely cyclic dynamics of positive and negative emotions an organism needs to respond to environmental opportunities and threats. We postulate that the mechanism of mood change projects over to macroeconomic dynamics. Our adaptation of the gated dipole is composed of the following equations:

$$\dot{x}_i = -x_i + I_b + I_{\Delta i}, \tag{1}$$

$$\dot{y}_i = b_i(1 - y_i) - c_i x_i y_i, \tag{2}$$

$$x_{i+2} = -x_{i+2} + x_i y_i, \tag{3}$$

$$\dot{x}_5 = -x_5 + (1 - x_5)x_3 - (x_5 + 1)x_4. \tag{4}$$

In Eqs. (1)–(3), $i = 1, 2$ is a subscript. All x variables are neuron activations described with a unitless version of the Hodgkin–Huxley equation. For $x_1, \ldots, x_4$ its special cases are used, while the general form is evident in x_5, a neuron receiving activating signals from x_3 and suppressing ones from x_4. Constants b_i and c_i are real positive numbers, I_b is 'tonic' signal putting the system in optimal working condition, and $I_{\Delta 1}$, $I_{\Delta 2}$ are external inputs. This is the most parsimonious gated dipole to account for economic growth and slump.

We illustrate our approach with three examples. First is Montenegro, a small country in Southeast Europe, which declared independence in 2006 and has a short data history. In addition, the next years its economy was hit by the global recession, further complicating any potential prediction effort. Two other examples, Germany and France, show that our modelling technique successfully competes with the conventional forecasting tools, proving that large economies can also exhibit 'emotion-type' fluctuations.

We work with annual Eurostat data for the following nine macroeconomic aggregates: gross domestic product (GDP), and its components: gross fixed capital formation (GFCF, or 'investment' for short), household final consumption expenditure (HFCE, or simply 'household consumption'), individual government consumption, collective government consumption, export of goods, export of services, import of goods, and import of services. The data's annual first differences are used, which is a conventional trend-removing technique. Examples with forecasting the GDP, investment, and household consumption are shown here, and predictions of the other six are similar. The model receives as independent variables combinations of the GDP components for year t. The predicted variable is taken in year $t + 1$. In short, we plug in the model one year's data to make it learn (in calibration mode) a following year's datum. In testing mode, this year's data is the input to produce next year's forecast.

For each model's subset of independent variables, two sums for the positive and negative annual changes are formed. We postulate that these are analogous to the positive and negative emotions in the brain neural circuit. These sums are:

$$S^{+}(t) = \sum_{j=1}^{n} [u_j(t)]^{+}, \tag{5}$$

$$S^{-}(t) = \sum_{j=1}^{n} [u_j(t)]^{-}, \tag{6}$$

where u_j are the first-difference data of each economic indicator, while n is the number of predictors in the concrete model, whereby $n = 1, \ldots, 8$. The operators with brackets are defined as $[\xi]^{+} = \max(\xi, 0)$, and $[\xi]^{-} = \min(\xi, 0)$. As all quantities in Eqs. (5)–(6) are in millions of euros, they are rescaled with coefficient $\alpha_1 = 1/10000$ to fit in the range of neural signals, and are used in forming the model inputs:

$$I_{\Delta 1}(t) = \begin{cases} \alpha_1(S^{+}(t) + S^{-}(t)), & S^{+}(t) + S^{-}(t) \geq 0 \\ 0, & S^{+}(t) + S^{-}(t) < 0 \end{cases}, \tag{7}$$

$$I_{\Delta 2}(t) = \begin{cases} \alpha_1(S^{+}(t) + S^{-}(t)), & S^{+}(t) + S^{-}(t) < 0 \\ 0, & S^{+}(t) + S^{-}(t) \geq 0 \end{cases}. \tag{8}$$

The value of α_1 is determined by the size of each country's economy. Signals $I_{\Delta 1}(t)$ and $I_{\Delta 2}(t)$ are $I_{\Delta i}$ in Eq. (1).

The system of Eqs. (1)–(4) can be solved with sufficient precision by introducing some simplifying assumptions [10] that allow computing the fast neural activations x_i at equilibrium as per Eqs. (9)–(11) below. The slow $y_i(t)$ transmitters have been solved with a numerical method, or more recently, with a special-case analytical solution [11] shown in Eq. (12). The neurocomputational model then becomes:

$$x_i(t) = I_b + I_{\Delta i}(t), \tag{9}$$

$$x_{i+2}(t) = x_i(t) y_i(t) \tag{10}$$

$$x_5(t) = (x_3(t) - x_4(t))/(1 + x_3(t) + x_4(t)), \tag{11}$$

$$y_i(t) = y_i(t-1)\exp[-c_i x_i(t) - b_i] + \frac{b_i}{b_i + c_i x_i(t)} \{1 - \exp[-c_i x_i(t) - b_i]\}. \tag{12}$$

Here t is discrete time, set to $1/10$ of a year for convenience in computation. The model forecast, originally a 'neural signal', is calculated as $\zeta_t = \alpha_1^{-1}/x_5(10t)$ with α_1 scaling it back into economic variable measured in millions of euros. The actual prediction is every 10th value of x_5 because time enough is given to transmitters y_1 and y_2 to adapt. The idea is that GDP data are announced at low frequencies but meanwhile the economic processes slowly carry on, an effect captured in the model by the slowness of its neurotransmitter elements.

Constants b_1, b_2, c_1, and c_2 are found in a simulated annealing procedure minimizing the following objective function:

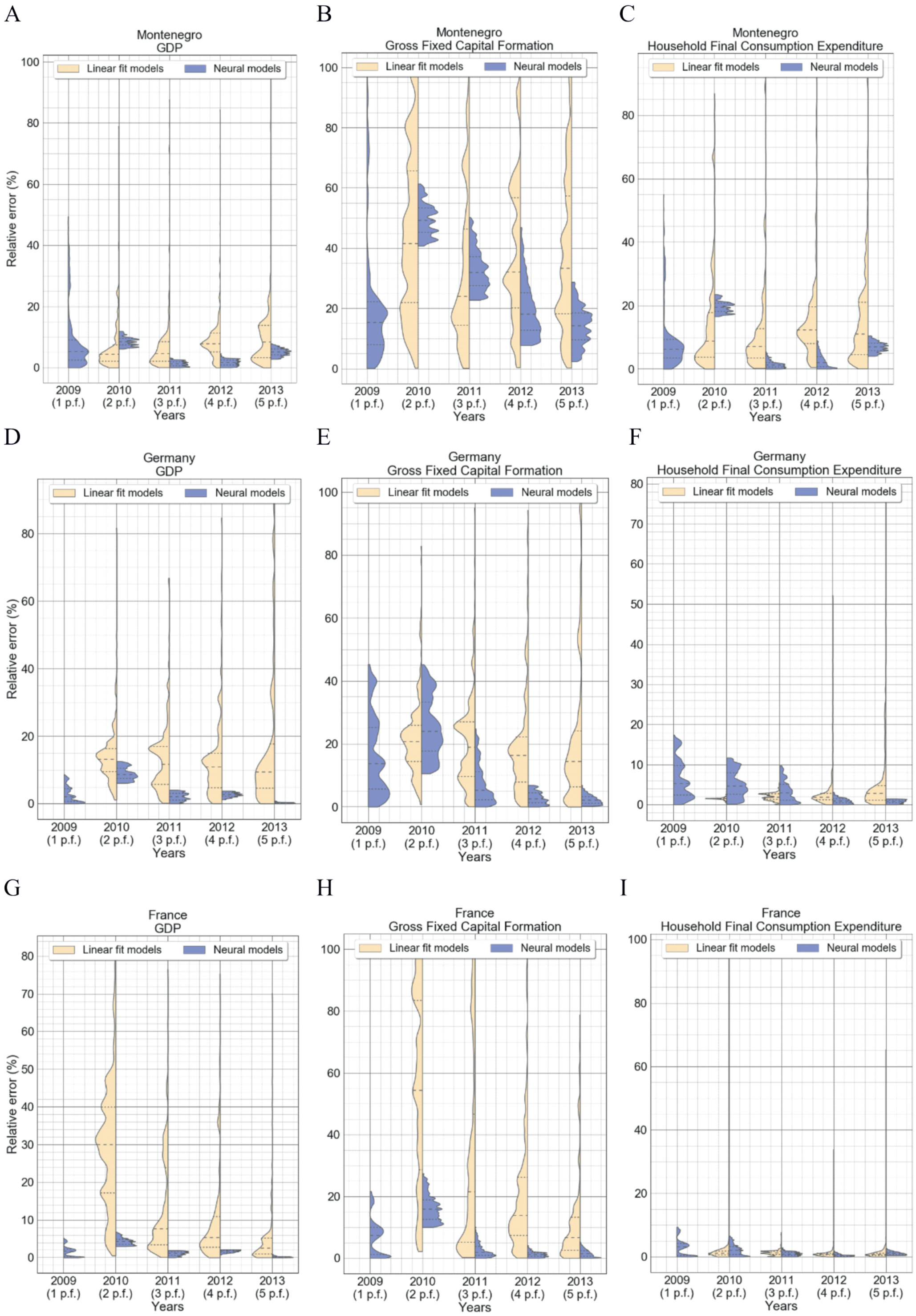
$$J = \min \left[\sum_{t=1}^{m-1} \left| \frac{u_{t+1} - \zeta_t}{u_{t+1}} \right| \right]. \tag{13}$$

Alternative versions of J with only $|u_{t+1} - \zeta_t|$ or $(u_{t+1} - \zeta_t)^2$ in the sum of Eq. (13) produce almost the same forecasting accuracy. Here, m is the number of points used for calibration, a concept whose explanation follows.

With no previous data for Montenegro, the model can start with as little as one point in time to learn, before producing a first forecast. That amounts to taking a vector of predictor values for 2007 and making the model connect it with a dependent variable's value in 2008. Therefore, to test a calibrated model would mean to submit the 2008 predictor vector and have a prediction for 2009. That is a one-point forecast (1 p.f.), the extreme case. Similarly, when two consecutive points are utilised for training, in 2010 one has a 2 p.f. For the latter year, linear fit models are already possible. They are run here for the sake of comparison, being the most conventional tool in econometrics. While such tiny samples do not allow for significance assessment of regression coefficients or overall model adequacy, another kind of estimate is available. With a set of $n = 8$ independent variables, the number of combinations they can enter as singles, couples, triples, etc. is $\sum_{i=1}^{n} \binom{n}{k}$, or 255 in total. These are the linear-fit models whose empirical distribution of relative errors' absolute values for Montenegro is shown in the top row of Fig. 2, left semi-violin plots, starting in 2010. With the error staying mostly within 20% for GDP and within 25% for household consumption, this linear-fit forecasting looks less desperate than expected given the scarcity of data.

Results. The neural models' performance with the same 255 input combinations is shown in the right semi-violin plots. To begin with, this technique is capable of a single-point forecast in which it is similar – at least in spirit – to the Cauchy method for solving differential equations with an initial condition. Second, most of the time their error distribution beats the linear fit both in terms of smaller magnitude and in terms of lower variance. We conducted Wilcoxon Matched-Pairs Tests over the distributions' medians for 2010–2013 and found statistically significant differences in 34 of all 36 comparisons in Fig. 2. The neural model was better in 27 cases, the linear fit in 7, and in two the difference was not significant. This is a preliminary result as it involves only three macroeconomic variables for only three countries. A further study must identify the realistic capabilities of the proposed neural circuit modelling, yet its prospects look positive.

As the investment forecasts show (Fig. 2, top row, middle), the neural models can rapidly improve their accuracy over a few years. What they cannot do eventually, is anticipate external shocks such as those that caused the recession and its aftereffects, accounting for the error biases in 2010.



A
Montenegro
GDP
B
Montenegro
Gross Fixed Capital Formation
C
Montenegro
Household Final Consumption Expenditure
D
Germany
GDP
E
Germany
Gross Fixed Capital Formation
F
Germany
Household Final Consumption Expenditure
G
France
GDP
H
France
Gross Fixed Capital Formation
I
France
Household Final Consumption Expenditure
Linear fit models
Neural models
Relative error (%)
2009 (1 p.f.)
2010 (2 p.f.)
2011 (3 p.f.)
2012 (4 p.f.)
2013 (5 p.f.)
Years

← Fig. 2. Forecasting macroeconomic variables for three European countries. Each plot presents error distributions of 255 linear-fit models (left semi-violins) and 255 dipole neural models (right semi-violins). Dotted lines show medians and quartiles. Notations 1 p.f., 2 p.f., etc., stand for forecast, based on a single previous point, two previous points, etc., as explained in the text. Linear-fit outliers, typically 1–5% of all data, are not shown. **A, B, C**: Montenegro; **D, E, F**: Germany; **G, H, I**: France

Observing the forecasts for Germany and France (Fig. 2, middle and bottom rows) yields further insights. The best conventional forecasts are based on a lot more observations and achieve error around 5–6% in years of turmoil [1,2]. The fact that a neurocomputational model is generally equal to and at times better than that suggests that macroeconomic dynamics might indeed be composed of a mixture of processes, similar to the neural dynamics of emotions.

Discussion. Overall, the error variance of the set of 255 neural models is a great deal smaller than that of the linear-fit models. This achievement can be explained by a classical tenet of machine learning, the bias-variance dilemma [12]. It is known that for a given task, the sum of the error bias and the error variance is constant for any modelling or approximating function, and reducing one is at the expense of the other. The problem can be solved only by "designing the right biases", in the formulation of the authors of [12]. The same concept is sometimes called "inductive bias" or "speculative bias", and identical meaning is put by the natural sciences in the term "mechanistic model", i.e., a theoretical construct capturing the mechanism of a phenomenon. In our case, the guiding theory is the fractal-type analogy, underpinning the knowledge transfer from a neural circuit for emotions to macroeconomic ups and downs. Its overall success shown in Fig. 2 suggests that it has indeed added another facet to the understanding of macroeconomic dynamics.

All the same, neurocomputation is less convincing for 2009 and 2010 as compared to the other years, possibly due to the recession. However, its effect is absorbed already in the three-point forecasts, except for Montenegro's investment. An explanation of the latter could be lower data quality and/or the larger investment volatility typical for small economies. The model shows impressive performance in the case of France, suggesting that this country's economic cycle resembles emotional neurodynamics a lot. Interestingly, while the German GDP is finely captured, less so are its investment and household consumption. The reason for that is unknown, yet a hypothesis points to the country's internal economic dynamics after the absorption of East Germany.

Conclusion. Because emotions influence short-run economic dynamics, a neural circuit model for affect helps clarify how businesses form their expectations that give rise to aggregate outcomes. This is especially valuable in times of turbulence when clarity is scarce and high-quality forecasts are most needed. Methodologically, this transfer of knowledge from neuroscience to economics may be viewed as a semi-empirical theory, implementing the socioeconomic fractality principle.

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