Interpretable Neural Networks for Panel Data Analysis in Economics *

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Abstract

The lack of interpretability and transparency are preventing economists from using advanced tools like neural networks in their empirical work. In this paper, we propose a new class of interpretable neural network models that can achieve both high prediction accuracy and interpretability in regression problems with time series cross-sectional data. Our model can essentially be written as a simple function of a limited number of interpretable features. In particular, we incorporate a class of interpretable functions named persistent change filters as part of the neural network. We apply this model to predicting individual’s monthly employment status using high-dimensional administrative data in China. We achieve an accuracy of 94.5% on the out-of-sample test set, which is comparable to the most accurate conventional machine learning methods. Furthermore, the interpretability of the model allows us to understand the mechanism that underlies the ability for predicting employment status using administrative data: an individual’s employment status is closely related to whether she pays different types of insurances. Our work is a useful step towards overcoming the “black box” problem of neural networks, and provide a promising new tool for economists to study administrative and proprietary big data.

1 Introduction

Traditionally, economists have relied on interpretable models like linear regressions and logistic regressions, which provide clear insights on the causal or statistical relationships in small datasets [1, 20]. Recently, the use of administrative and proprietary big data has led to some exciting work in empirical economics [14, 13, 5, 15, 18]. Though such datasets enjoy the richness of variables and large sample size, advanced tools like neural networks have not been adopted widely in their analysis as was originally expected [7]. Methodologically, there have been some attempts to bring machine learning tools to economic analysis. However, most of those successful applications are limited to relatively simple models like Lasso, ridge regressions or decision trees [16, 2, 11]. Economists are still nervous about using more advanced tools like neural networks, since they mostly deliver outcomes from a complicated black box without transparency or interpretability [2], even though they are more accurate than conventional models.

To address this dilemma, we propose a new class of interpretable neural network models to study panel data [4]. Our model allows us to take advantage of the high accuracy of neural networks, while

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**Panel data are “data with a cross section of units with repeated observations on them over time”’. It is also called time series cross-sectional data. In this paper, we will use these two names interchangeably.

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remaining interpretable like linear or logistic regressions. To this end, we design a modified version of neural networks, which only consists of limited compositions of interpretable and differentiable operators on a limited number of variables. A key feature of our model is that we can incorporate interpretable function forms with unknown parameters as part of the neural network. In this paper, we incorporate a class of persistent change filters as part of the network, which turns out particularly helpful in time series cross-sectional data analysis. Besides constructing the interpretable features from function compositions, we also require the final model to take only a small number of effective features, by incorporating a penalty term in the loss function. The comparison between our model and conventional neural network model is illustrated in Figure 1 and we will present the detailed model setup in Section 2.1.

![Comparison of Conventional Neural Networks (left) and Interpretable Neural Networks (right).](image)

The model we propose in this paper has three main virtues. First, it is easy to interpret. As is shown in the right panel in Figure 1, our model can essentially be written as a simple function of a limited number of interpretable features (the red circles), and the interpretable features arise from limited number of “neural network” type of function compositions. While training the model, we can generate the most informative interpretable features automatically, without doing feature engineering work by hand. Second, it has the nice architecture similar to conventional neural networks, which makes it powerful to fit the data patterns and can be trained efficiently using stochastic gradient descent (SGD) algorithms. We will illustrate the prediction power of this model in our application in Section 3. Third, our model is quite robust and stable subject to data missing problems, which is a critical feature of interpretable models.

As an application, we use the interpretable neural network models to predict individual’s monthly employment status using high-dimensional administrative data in China. We achieve an accuracy of 94.5% on the test set, which is comparable to the best-performed conventional machine learning methods. In addition, we clearly understand how the model predict an individual’s employment status with her payment records of different types of insurances. Both the accuracy and the interpretability are robust subject to data missing problems.

This paper contributes to the literature with the following distinct features. First, we expand the machine learning toolbox for economists [16, 4, 11] by introducing a modified version of neural networks that achieve high accuracy without sacrificing interpretability and transparency. Second, we contribute to the large literature on interpretable machine learning. Previous work in computer vision and natural language processing [6, 23, 12] mostly focus on interpreting how hidden units of neural networks represent local features of images and texts. In this paper, we propose an interpretable model to study time series cross-sectional data, to help people understand the mechanisms behind the collective human behavior. In the terminology of the overview paper on interpretable machine learning by [17], our model delivers “model-based interpretability”, which is different from work that delivers “post hoc interpretability” by approximating outcomes from complicated models with simple functions. Last but not least, the application of our model to predicting individual employment status with China’s administrative data also contribute to the large literature on China’s unemployment rate estimation in the absence of reliable official statistics [9, 8]. Our work stands out in this literature as
a novel application of machine learning methods on administrative big data, rather than traditional accounting procedure on household survey data.

The remaining of the paper is organized as follows. In Section 2, we present the architecture and training algorithms of our model. In particular, we encode a class of interpretable functions named persistent change filters. In Section 3 we apply the model to an administrative dataset to predict individual’s employment status in China. Finally we conclude with discussions on the future work.

2 Interpretable Neural Networks for Panel Data

2.1 Mathematical Formulation

Consider a model $y_{it} = g(x_{it}, \theta)$, where $y_{it}$ is outcome for observation $i$ at time $t$ and $x_{it}$ is high dimension inputs. We hope to construct an interpretable function $g(\cdot, \theta)$, which is a composition of several operators as $g = g^{(M)} \circ g^{(M-1)} \cdots \circ g^{(1)}$. Here we choose $M = 4$. $\{g^{(m)}\}$ are basic components defined as below with undetermined parameters to be trained in the neural network.

1. $g^{(1)}$: Decision-tree-like splitting $Sp(x) = \text{Sigmoid}(px + q)$. For $x \in \mathbb{R}^1$, a sigmoid function can function as a decision-tree-like splitting operator like a differentiable indicator function [21]. For example, if $p$ is close to 1 and $q$ is a large negative number, the output can be close to 0 and 1 to discriminate whether $x$ is smaller or larger than a threshold. Here $p$ and $q$ are unknown parameters.

2. $g^{(2)}$: Dimension reduction $Re(x)$. For $x \in \mathbb{R}^m$, define $Re(x) : \mathbb{R}^m \rightarrow \mathbb{R}^n (n < m)$ as a certain dimension reduction function with unknown parameters. For example, $Re(x)$ could be linear combination with sparse inputs, and the linear coefficients are unknown parameters.

3. $g^{(3)}$: Other interpretable transforms $Trans(x)$. For $x \in \mathbb{R}^n$, we can propose other transforms to generate interpretable features and incorporate them into the model. In the next section, we introduce a general class of interpretable transforms named persistent change filter, which turns out helpful in regressions with panel data. $Trans(x)$ also include unknown parameters.

4. $g^{(4)}$: simple linear or logistic function as the final layer. The effective inputs of the final layer are required to be sparse, by adding a penalty term in the loss function.

Our model can essentially be written as a simple function $g^{(4)}$ of a limited number of interpretable features (outcomes of $g^{(3)}$), which makes it easy to interpret. Its structure as the composition of differentiable functions makes it easily trainable as conventional neural networks.

2.2 A General Class of Features for Time Series Data: Persistent Change Filter

For a particular time series for some certain observation (the $i$ subscript is omitted here for simplicity), $x_\tau \in [0,1], \tau = 1, 2,...,T$, we define the persistent change filter $D = p_1 - q_t$, where:

$$p_1 = x_1, p_{\tau+1} = x_{\tau+1} + k x_{\tau+1} p_\tau + (1-k) p_\tau$$

$$q_1 = 1 - x_1, q_{\tau+1} = (1 - x_{\tau+1}) + k (1 - x_{\tau+1}) q_\tau + (1-k) q_\tau$$

Here $k \in [0,1]$ is a smoothing parameter. Then we can map the original time series $\{x_t\}, t = 1, 2,...,T$ to a persistent change filter time series $D(\{x_\tau\}_{\tau=1}^T), t = 1, 2,...,T$. The definition of the persistent change filter $D$ is motivated by identifying a persistent change in time series data. We illustrate this idea first with two examples and formalize with a proposition.

Example I For a binary time series $x_t \in \{0, 1\}, t = 1, 2,...,T = 1000$. $x_t$ begins with 0 for some periods, and persistently switch to 1 for the last $t_0$ periods: $x_t = 1 \{t > T - t_0\}$. We plot the persistent change filter on the entire time series $D(\{x_\tau\}_{\tau=1}^T)$ against the number of periods $t_0$ between the transition and the terminal period in the left panel of Figure 2. We find that no matter what smoothing variable $k$ we choose, the persistent change filter fits perfectly with $t_0$ on the 45° line. This implies that the persistent change filter captures the duration of a persistent change in such a binary time series 0, ..., 0, 1, 1, ..., 1.

Example II In real world, such perfect binary data may not exist. Consider time series $x_t$, where everything is the same as Example I, except that a random 5% of $x_t$ are replaced by abnormal data as
Persistent Change Filter on Data without Missing Problems

Figure 2: Persistent Change Filter Captures the Duration of a Persistent Change

\[ x_t = 0.9 \quad \text{when} \quad t > T - t_0. \]

Then we plot the persistent change filter \( D(\{x_t\}) \) against \( t_0 \) for different choices of the smoothing parameter \( k \) in the right panel of Figure 2. For the persistent change filter without any smoothing (i.e. \( k = 1 \)), the plot deviates from the 45\(^\circ\) line significantly. When \( k \) decreases, the plot get closer to the 45\(^\circ\) line. So an optimal choice of \( k \) would help capture the duration of a persistent change in such a time series with potential data missing. To note, \( k \) would be left as an unknown parameter that our model would learn from the data.

We formalize the examples above with the following proposition:

**Proposition 2.1.** When \( k \to 1 \), \( p_T \) uniformly converges to \( D^{(0)} \) defined as below:

\[
D^{(0)}(x_T, x_{T-1} \ldots x_1) = \sum_{i=1}^{T} \prod_{j=1}^{i} x_{T-j+1}.
\]

What does \( D^{(0)} \) means for the time series? Consider the binary time series \( x_t \in \{0, 1\}, t = 1, 2 \ldots T \), \( D^{(0)} \) is the lasting time periods for recent \( x_i \)'s to be 1. In other words,

\[
D^{(0)}(x) = m \iff x_T = x_{T-1} \ldots = x_{T-m+1} = 1, x_{T-m} = 0
\]

Thus \( D^{(0)} \) gives information on the lasting time since the most recent period when the binary time series persistently switch to 1. For continuous \( x_t \) in \([0, 1]\), \( D^{(0)} \) is differentiable at any point, which means it could be part of a trainable model. However, \( D^{(0)} \) only captures the jumps from low values to high values, so we extend \( D^{(0)} \) to \( D \) so that it can capture both persistent jumps and drops in the time series. This is the \( q_T \) term in the formulation. As is discussed above, we also add the trainable smoothing parameter \( k \) to adjust for missing or abnormal data problems. For a more elaborate discussion and the origins of the persistent change filter, please refer to Supplement D.

2.3 Composition and Training

With the components above, we can give a full architecture of \( g \). Suppose \( X = (X_1, \ldots X_m) \) is an \( m \)-dimension vector as the original input, we have

\[
X^{(1)} = g^{(1)}(X, \theta^{(1)}) = (\text{Sp}(X_1), \text{Sp}(X_2) \ldots \text{Sp}(X_m))
\]

\(^3\)Some might find the idea of the persistent change filter seems related to the structural break literature in time series analysis. However, the structural break detection methods are not applicable for feature constructions, since they mostly focus on detecting break points with formal statistical tests, while we hope to get an explicit function transform as part of the interpretable model.
\[
X^{(2)} = g^{(2)}(X^{(1)}, \theta^{(2)}) = \text{Re}(X^{(1)})
\]
\[
X^{(3)} = g^{(3)}(X^{(2)}, \theta^{(3)}) = \text{Trans}(X^{(2)})
\]
\[
y = g^{(4)}(X^{(3)}, \theta^{(4)})
\]

Thus we have \( g = g^{(4)} \circ g^{(3)} \circ g^{(2)} \circ g^{(1)} \). The full architecture of interpretable neural network function \( g \) is in the right panel of Figure 1. It is easy to interpret since it can be written as a simple function of a small number of interpretable features (red circles), which arise from limited number of “neural network” type of function compositions.

Finally, we add Lasso 19 or group Lasso 22 penalty to the loss function to require sparse input:

\[
L(\theta, \phi) = \mathbb{E}_{X,Y} \text{Loss}(g(x, \theta), y) + \text{penalty}(g^{(4)})
\]

Since all components are differentiable in loss function 1, the model can be trained like a conventional neural network with Adam 10.

3 Application to Administrative Data

3.1 Employment Status Prediction with Administrative Data

In this section, we apply the interpretable neural network model to predict individual’s monthly employment status using high-dimensional administrative data as input. The administrative data comes from a four-million city in China 4 and includes basic demographic information (age, family relations, gender, education, etc.), as well as individual level monthly payments to six different kinds of social insurances and the Housing Provident Fund (HPF). With all these features, together with employment/unemployment labels on part of the sample (about 400,000 individuals are labelled every month), we construct an interpretable neural network model to predict employment status of all the individuals in the population each month. With the prediction results, we can calculate unemployment rate on the whole population as an important economic indicator for policy makers. This application is novel and important given the unreliability of China’s official unemployment statistics 8.

For individual \( i \) in calendar month \( t \), her employment status is denoted as \( y_{it} \in \{0, 1\} \), where 1 means employment and 0 means unemployment. Her payment amounts for different insurances, among other individual features are denoted as \( x_{itj} \) where \( j = 1, 2...m \) correspond to different features. To predict \( y_{it} \), we stack features of the individual in the past \( t_0 \) period as model inputs, denote as \( X_{it} = (x_{itj}) \) where \( j = 1, 2...m, \tau = t, t-1, ..., t-t_0 + 1 \). We assume the model is invariant to time \( t \), which means \( P(y_{it} = 1 | X_{it}) = f(x_{it}), \forall i, t \). For standard machine learning, \( f(\cdot) \) is usually complicated and requires feature engineering. In this paper, we will follow Section 2 to set up a more interpretable model to predict \( y_{it} \) with high accuracy.

3.2 Interpretable Neural Network Model Setup

Following Section 2, we write the model as \( P(y_{it} = 1 | X_{it}) = g(x_{it}, \theta) \) where \( g = g^{(4)} \circ g^{(3)} \circ g^{(2)} \circ g^{(1)} \). In this example, the interpretable transform \( g^{(3)} \) is the persistent change filter. Suppose the original input variables of \( g \) is a \( mt_0 \times 1 \) vector:

\[
x_{it} = (x_{ij\tau}) \text{ where } j = 1, 2...m, \tau = t, t-1, ..., t-t_0 + 1.
\]

\( m = 7 \) is the number of insurances to pay and \( t_0 = 6 \) denotes the lagged periods we consider in model inputs. We define the detailed form for \( g = g^{(4)} \circ g^{(3)} \circ g^{(2)} \circ g^{(1)} \) as below:

4For confidentiality, we would not release any city-specific information including the city name in this paper.

5In China, there are five major types of social insurances: endowment insurance, basic medical insurance, unemployment insurance, employment injury insurance, and maternity insurance. For urban residents, basic medical insurance consists of “basic medical insurance for working urban residents” and “basic medical insurance for non-working urban residents”. Together with the Housing Provident Fund (HPF), which we take as one type of insurance from now on, our administrative data include detailed individual level payments to seven types of insurances in total. To note, those who pay for employment injury insurance or unemployment insurance are not necessarily employed or unemployed, and vice versa.
1. Decision-tree-like splitting $g^{(1)} : \mathbb{R}^{mt_0} \rightarrow \mathbb{R}^{mt_0}$.

$\hat{x}^{(1)}_t = (x^{(1)}_{ij})_t = g^{(1)}(\hat{x}_t, \theta^{(1)}) = \{Sp(x_{it1}), Sp(x_{it2}), \ldots, Sp(x_{itm, t-t_0+1})\}$ with $j = 1, 2, \ldots, m$, $\tau = t, t-1, \ldots, t-t_0+1$. Here the $\mathbb{R}^{1} \rightarrow \mathbb{R}^{1}$ splitting function $Sp(x) = \text{Sigmoid}(px + q)$. The trainable parameters $\theta^{(1)} = \{p, q\}$ are shared for different dimensions.

2. Dimension reduction $g^{(2)} : \mathbb{R}^{mt_0} \rightarrow \mathbb{R}^{t_0}$.

$\hat{x}^{(2)}_t = (x^{(2)}_{ij})_t = g^{(2)}(\hat{x}^{(1)}_t, \theta^{(2)}) = (\text{Re}(x^{(1)}_{1t}), \text{Re}(x^{(1)}_{2t-1}), \ldots, \text{Re}(x^{(1)}_{m, t-t_0+1}))$ This step is dimension reduction for the $m$-dimensional variables $x^{(1)}_t$ for a given $\tau$. Here the $\mathbb{R}^{m} \rightarrow \mathbb{R}^{1}$ function $\text{Re}(Z) = \text{Sigmoid}(w^TZ + b)$. The trainable parameters are $\theta^{(2)} = \{w, b\}$. In our example, $w$ will be interpreted as the contribution of each kind of insurance or HPF payment to the variable where we are going to calculate the persistent change filter.

3. Interpretable transform: persistent change filter $g^{(3)} : \mathbb{R}^{t_0} \rightarrow \mathbb{R}^{1}$.

For the final component of $g$, we use a simple form of logistic regression: $P(y_{it} = 1) = g^{(4)}(\hat{x}^{(3)}_t, \theta^{(4)}) = \text{Sigmoid}(w^T\hat{x}^{(3)}_t + v)$ where trainable parameters are $\theta^{(4)} = \{u, v\}$. As $g^{(3)}$ gives a one-dimensional output, we omit the penalty on $g^{(4)}$.

With all components above, we can get the interpretable neural network model as $g = g^{(4)} \circ g^{(3)} \circ g^{(2)} \circ g^{(1)}$. The loss function is $\mathbb{E}(- \log P(y_{it} | x_{it}))$, where $\mathbb{E}$ means taking average over all the data observations $(x_{it}, y_{it})$. $\theta = \{p, q, w, b, k, u, v\}$ is the set of all the trainable parameters in the model. The final value for these parameters would deliver the concrete form of the full model $g$.

### 3.3 Dataset and Model Results

With the administrative data in Section 5.1, we use monthly payment data of various social insurances and the HPF from July 2016 to December 2017 to construct $x_{it}$. To construct a balanced data sample, we randomly select 20,000 employed observations and 20,000 unemployed observations to get a balanced sample. Both positive and negative samples are evenly divided into two parts to get the training set and the test set.

For performance evaluation, we will consider other interpretable models (logistic regressions) as well as more complicated models (random forests). These models require handcrafted features as model inputs. Based on the descriptive statistics and domain knowledge (see the details in Supplement A), on this problem, we construct the following features:

1. “Insurance count” (IC). The number of types of insurances the individual pays in period $t$.
2. “Naive persistent change” (NPC). For each kind of insurance, we construct the “naive persistent change” $D^{(0)}(x_{it}, x_{i,t-1}, \ldots, x_{i, t-t_0+1})$ following the definition in Proposition 2.1 where $x_{it}$ is a binary variable on whether the individual does not pay for a specific insurance in period $\tau$. Compared to the persistent change filter measure, these “naive” measures do not incorporate any trainable parameters, and come directly from feature engineering.
3. “Payment change” (PC). We construct another “naive persistent change” variable taking the same expression based on the following binary time series $x_{i\tau}$: whether the number of types of insurances the individual has paid is larger than 2. The feature with threshold 2 is constructed with insights from the descriptive statistics (see Supplement A).

With these features in hand, we compare the performance of the following 11 models:

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6 We omit neural networks with different hyperparameters here because their accuracy is worse than the random forests in the test set.

7 As is discussed in Proposition 2.1, $D^{(0)}$ only works for increasing time series ..., 0, 0, ..., 0, 1, ..., 1. So here we define $x_{i\tau}$ as whether the individual does NOT pay, rather than pay a specific insurance in period $\tau$. The persistent change measure that captures both jumps and drops is derived in the D.
1. The interpretable neural network (IntNN) model (1) we propose in this paper. No handcrafted feature is needed in this model.
2. Logistic regression (Logistic) with (2) 7 “naive persistent changes”, “payment change” and insurance count; (3) 7 “naive persistent changes”; (4) “payment change” and insurance count; (5) “payment change”; (6) insurance count.
3. Random forests (RF) with (7) 7 “naive persistent changes”, “payment change” and insurance count; (8) 7 “naive persistent changes”; (9) “payment change” and insurance count; (10) “payment change”; (11) insurance count.

The results of model performances are in Table 1.

Table 1 shows that the model we propose (first row) achieves the highest accuracy. Models based on random forest algorithm and feature engineering enjoys higher accuracy than logistic regressions, but are not transparent for interpretation. Traditional interpretable models like logistic regressions perform much worse in terms of accuracy.

3.4 Model Interpretation

The interpretable neural network models deliver a clear mechanism behind the model outcome. Now we will look into the model estimation results, and interpret the model we obtain. We look into the model parameters for each component of $g = g^{(4)} \circ g^{(3)} \circ g^{(2)} \circ g^{(1)}$.

1. Decision-tree-like splitting $g^{(1)}$: For $\forall j, \tau, x_{i\tau j}^{(1)} = \text{Sigmoid}(p x_{i\tau j} + q)$.
   The estimates are $p = 2.60, q = -41.46$. As is discussed in Section 2.1, with such $p$ and $q$, $g^{(1)}$ would transform small payment values to 0, while keep large payment values close to 1. So, it approximates an indicator function.

2. Linear combination $g^{(2)}$: For $\forall \tau, x_{i\tau}^{(2)} = \text{Sigmoid}(w^T x_{i\tau j}^{(1)}) + b$.
   The estimates of the $m$-dimensional vectors $w = (-1.73, 1.84, -4, 0.64, 0.62, -0.66, 0.65, 4.19)^T$, and each element corresponds to endowment insurance, urban working medical insurance, unemployment insurance, employment injury insurance, maternity insurance, urban non-working medical insurance, and the Housing Provident Fund (HPF) respectively. The intercept $b = 3.67$. In this layer, we build up a 1-dimension variable $x_{i\tau}^{(2)}$ from the linear combination of the 7-dimensional payment records after the decision-tree-like splitting. The output is positively correlated with payments of urban working medical insurance, employment injury insurance, maternity insurance, and the Housing Provident Fund (HPF), while negatively correlated with payments of endowment insurance, unemployment insurance, urban non-working medical insurance.

3. Persistent Change Filter $g^{(3)}$, $x_{i\tau}^{(3)} = D((x_{i\tau}^{(2)})_{t-b}^{t+1}, k)$.
   The estimated smoothing parameter is $k = 0.9999999$. As we show in Proposition 2.1, $k \to 1$ means no smoothing for data missing or abnormal data pattern is imposed for the persistent change filter. Thus this is a persistent change filter directly on $x_{i\tau}^{(2)}$, and larger value corresponds to a persistent jump of $x_{i\tau}^{(2)}$, while smaller value corresponds to a persistent drop of $x_{i\tau}^{(2)}$.

4. Logistic regression $g^{(4)}$: $P(y_{i\tau j} = 1) = \text{Sigmoid}(u x_{i\tau j}^{(3)} + v)$
   The estimates are $u = 1.06, v = -2.18$. This is a differentiable version of linear transform with coefficient close to 1, so it is similar to identity.

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*We also compare $w$ with parameters from logistic regression models, and find they share qualitatively the same interpretation while our model obtains higher accuracy. See Supplement B for more details.*
To summarize, our interpretable neural network model predicts individual’s employment status simply with the *persistent change filter* of a composite variable from a linear combination of whether an individual pay each type of insurance. The weights of the linear combination imply the relative importance of each insurance when predicting the employment status. From the model, we learn that when an individual that used to consistently pay urban working medical insurance, employment injury insurance, maternity insurance, or the Housing Provident Fund (HPF), but suddenly drop out from those insurance programs, has a larger chance to become unemployed. Similarly, for individuals that are beginning to get enrolled in endowment insurance, unemployment insurance, urban non-working medical insurance, they have a larger chance to get unemployed.

### 3.5 Robustness of the Model

As is discussed in [17], an interpretable model should be robust to data missing or abnormal data problem. We randomly set 10% of all the payment records to 0, and train the same 11 models as above and our model still perform the best in term of accuracy. Also, the parameter estimates deliver qualitatively equivalent interpretations. The value of parameter $k$ in the *persistent change filter* becomes smaller to balance missing. Please refer to Supplement C for more details.

### 4 Conclusion

The lack of interpretability and transparency are preventing economists from using neural networks in their empirical work. In this paper, we propose a new class of interpretable neural network models that can achieve both high prediction accuracy and interpretability in regression problems with time series cross-sectional data. Our model could essentially be written as a simple function of a limited number of interpretable features, which arise from limited number of “neural network” type of function compositions. In particular, we incorporate a class of interpretable functions named *persistent change filters* as part of the neural network. The model is easy to interpret by design, while is powerful enough to fit the data well due to similar architecture as conventional neural networks.

As an application, we use the interpretable neural network models to predict individual’s monthly employment status using high-dimensional administrative data in China. We achieve a high accuracy as 94.5% on the out-of-sample test set, which is comparable to the best-performed conventional machine learning methods. Furthermore, we interpret the model to understand the mechanisms behind. We find that it predicts individual’s employment status simply with the *persistent change filter* of a composite variable from a linear combination of whether an individual pay each type of insurance. From the model, we learn that when an individual that used to consistently pay urban working medical insurance, employment injury insurance, maternity insurance, or the Housing Provident Fund (HPF), but suddenly drop out from those insurance programs, has a larger chance to become unemployed. We compare our model with logistic regression models, and find the model interpretations are qualitatively the same, while our model delivers much higher prediction accuracy.

This paper propose a promising method to overcome the “black box” problem of neural networks, and contribute to the machine learning toolbox of economists by introducing a modified version of neural networks that is both accurate and easy to interpret. With the massive use of administrative and proprietary big data in economics and policy research, lots of research could be done with this new tool.

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Supplementary Materials

A Descriptive Statistics

Table 2 presents some descriptive statistics on insurance payment behaviors of both the employed and the unemployed sample. The upper panel is the number of employed and unemployed individuals that pay each type of the insurances in the most recent month in the sample. From this panel we can see that the unemployed individuals tend to pay endowment insurance, unemployment insurance and urban working medical insurance, while the employed individuals pay all the insurances except for urban non-working medical insurance, since they mostly prefer urban working medical insurance. The lower panel reports the number of types of insurances that paid by each employed and unemployed individual in the most recent month, we find that the employed individuals tend to pay more kinds of insurances. With the elbow method, we find 2 is a good threshold to discriminate the employed and the unemployed if we hope to do some traditional feature engineering, since most of the unemployed sample pay less or equal to 2 types of insurances.

B Interpretation Comparison: Our Model vs Logistic Regression

We compare our model with the logistic regression model with the “naive persistent changes” of seven kinds of insurances as model inputs. The definition of “naive persistent change” is in Section 3.3. The linear combination weights in $g^{(2)}$ of our interpretable neural network model and the logistic coefficients of each variable are in Table 3.

From Table 3 we find the interpretations of our model and the logistic regression model are qualitatively the same. As is discussed in the definition of “naive persistent change” in Section 3.3, larger naive persistent change means the individual switch from paying to not paying a specific type of insurance. Thus negative coefficients in the logistic regression imply a positive relationship between jumps in payments and the probability getting employed, which share the same interpretation as positive coefficients in our model. Here we find the signs of all the coefficients in the interpretable neural
networks are exactly opposite to each other, which means they share exactly the same interpretation qualitatively.

C Robustness of the Model

C.1 Model Accuracy with Data Missing

The model we propose is robust to data missing or abnormal data problems. To check the robustness, we randomly set 10% of all the payment records to 0 as data missing. Then we rerun the same 11 models as in Section 3.3. The model accuracy results are in Table 4.

| Index | Model | Inputs | Test Accuracy |
|-------|-------|--------|---------------|
| 1     | IntNN | -      | 0.92855       |
| 2     | NPC, IC, PC | 0.91735 |
| 3     | NPC   | 0.85805|
| 4     | PC, IC | 0.79235 |
| 5     | PC    | 0.7781 |
| 6     | IC    | 0.84025|
| 7     | NPC, IC, PC | 0.92715 |
| 8     | NPC   | 0.917  |
| 9     | PC, IC | 0.85645 |
| 10    | PC    | 0.84025|
| 11    | IC    | 0.84025|

From Table 4, we can see that all the results are similar subject to the 10% data missing. Though data missing makes all the models worse off, our interpretable model remain the best performance among all the competitors. In the next section, we will see the model parameters are also robust, which delivers robust model interpretation for the problem.

C.2 Model Interpretation with Data Missing

In Section 3.4, we interpret our model clearly through the model structure. Besides transparency of the model structure, robustness is another important feature of model interpretability. In this section, we illustrate the robustness of our model with model parameters we estimate with 10% missing data in Section C.

1. Decision-tree-type splitting $g^{(1)}$: For $\forall j, \tau$, $x_{ij\tau}^{(1)} = \text{Sigmoid}(px_{ij\tau} + q)$. The estimates are $p = 2.76, q = -43.96$, which are both close to those in the baseline model.

2. Dimension reduction $g^{(2)}$: For $\forall \tau$, $x_{i\tau}^{(2)} = \text{Sigmoid}(w^{T}(x_{i\tau}^{(1)})_{j=1}^{m} + b)$. The estimates of the m-dimensional vectors $w = (-0.76, 1.57, -2.12, 0.55, 0.5, -0.8, 3.39)^T$. The intercept $b = 2.87$. All the estimates are close to those in the baseline model.

3. Persistent Change Filter $g^{(3)}$: $\tilde{x}_{it}^{(3)} = D((x_{i\tau}^{(2)})_{\tau=t_0+1}^{t}, k)$. The estimated smoothing parameter is $k = 0.89$, different from the baseline estimates 0.999999. This is totally sensible: due to data missing, we need to impose some smoothing to get a reasonable persistent change filter time series that predict the outcomes well. This also confirms the rationale of the persistent change filter definition, as is detailed discussed in Supplement D.

4. Logistic regression $g^{(4)}$: $P(y_{it}) = \text{Sigmoid}(u\tilde{x}_{it}^{(3)} + v)$. The estimates are $u = 1.82, v = -5.96$, which are both close to those in the baseline model.

To summarize, our model is quite robust subject to data missing problems, and deliver essentially the same interpretations of the model outcomes.
D Motivation and Variants of Persistent Change Filter

The persistent change filter is a monotone reduction designed for univariate time-series input \( x = (x_1, x_2,...x_T) \), \( x_t \in \{0, 1\} \) and mainly captures the persistent jumps or drops in it.

D.1 Persistent change \( D^{(0)} \) for Binary Inputs

Consider the binary time series \( x_t \in \{0, 1\} \), \( t = 1, 2,...T \), persistent change is defined as the lasting time periods for recent \( x_t \)'s to be 1. In other words, \( D^{(0)}(x) = m \iff x_T = x_{T-1} = ... = x_{T-m+1} = 1 \), \( x_{T-m} = 0 \). This variable gives information on the moment the input turns into 1 and the lasting time.

D.2 Continuous Persistent change \( D^{(1)} \) for Continuous Inputs

When we have a continuous input \( x_t \in [0, 1] \), \( t = 1, 2,..., T \), we find a compatible expression for persistent change which reduces to the original version if we restrict the input to be binary.

\[
D^{(1)} = \sum_{t=1}^{T} \prod_{j=1}^{t} x_{T-j+1}
\]

In an iterative way, we can define a series \( p_t, t = 1, 2,..., T \) and \( p_1 = x_1, p_{t+1} = x_{t+1} + x_{t+1}p_t \), then we have the continuous persistent change measure \( D^{(1)} = p_T \). To understand the iterative definition, we see when \( x_{t+1} \) gets to 0, it will almost clean up the historical accumulation \( p_t \). When \( x_{t+1} \) remains to be 1, it will keep the historical accumulation \( p_t \) and \( p_{t+1} \) accumulates by adding \( x_{t+1} \).

D.3 Persistent change \( D^{(2)} \) : Symmetrical to Jumps and Drops

The measures \( D^{(0)} \) and \( D^{(1)} \) can only capture time series change from small values (like 0) to big values (like 1). To treat small and large values equally, we define a new measure \( D^{(2)} \) on continuous value time series \( x_t \in [0, 1] \), \( t = 1, 2,..., T \):

\[
p_1 = x_1, p_{t+1} = x_{t+1} + x_{t+1}p_t; q_1 = 1 - x_1, q_{t+1} = (1 - x_{t+1}) + (1 - x_{t+1})q_t
\]

\[
D^{(2)} = p_T - q_T
\]

In this definition, both jumps and drops in \( x_t \) are addressed.

D.4 Smooth Persistent change \( D^{(3)} \) : Adding a trainable smooth variable \( k \)

To weaken the cleaning-up effect against abnormal time series change due to missing data or data error problems, we define a smoothing variable \( k \in [0, 1] \), and define a new measure \( D^{(3)} \) on continuous value time series \( x_t \in [0, 1] \), \( t = 1, 2,..., T \):

\[
p^s_1 = x_1, p^s_{t+1} = x_{t+1} + kx_{t+1}p_t + (1-k)p_t
\]

\[
q^s_1 = 1 - x_1, q^s_{t+1} = (1 - x_{t+1}) + k(1 - x_{t+1})q^s_t + (1-k)q^s_t
\]

\[
D^{(3)} = p^s_T - q^s_T
\]

Compared to \( D^{(2)} \), the multiplication term \( x_{t+1}p_t \) is replaced by \( kx_{t+1}p_t + (1-k)p_t \). In other words, larger \( k \) means larger cleaning-up effect, while the accumulation effect is unaffected. When \( k = 1 \) we have \( D^{(3)} = D^{(2)} \). We leave \( k \) trainable to let the data finds the best value. Finally, we have the notion of persistent change filter \( D = D^{(3)} \).
D.5 Why Do We Call It Persistent Change Filter?

Consider four pairs of inputs:

\[ x^{(1)}_1 = (0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0), x^{(2)}_1 = (1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0); \]
\[ x^{(1)}_2 = (0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0), x^{(2)}_2 = (1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0); \]
\[ x^{(1)}_3 = (0.1, 0.1, 0.1, 0.9, 0.9, 0.9, ..., 0.9, 0.9), x^{(2)}_3 = (0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9), \]
\[ x^{(1)}_4 = (0.1, 0.1, 0.1, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9), \]
\[ x^{(2)}_4 = (0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9); \]

and the persistent change measures we defined above are in Table 5.

|       | \( D^{(0)} \) | \( D^{(1)} \) | \( D^{(2)} \), \( k = 0.25 \) | \( D^{(3)} \), \( k = 0.25 \) |
|-------|---------------|---------------|-------------------|-------------------|
| \( x^{(1)}_1 \) | 12            | 12            | 12, 11.90         | \( x^{(2)}_1 \) 0 | 0 | -12 | -11.90 |
| \( x^{(1)}_2 \) | 4             | 4             | 4, 8.81           | \( x^{(2)}_2 \) 0 | 0 | -4  | -8.81  |
| \( x^{(1)}_3 \) | -             | 6.49          | 6.37, 9.06        | \( x^{(2)}_3 \) - | 0.11 | -6.37 | -9.06 |
| \( x^{(1)}_4 \) | -             | 3.47          | 3.36, 6.90        | \( x^{(2)}_4 \) - | 0.111 | -3.36 | -6.90 |

From Table 5 we have the following intuitive findings as below:

1. As is shown in the first two rows, \( D^{(1)} \) is equivalent to \( D^{(0)} \) for binary inputs, while it can also handle continuous inputs as the last two rows.
2. \( D^{(2)} \) captures the persistent change idea, but is vulnerable to abnormal data points, as is in the second and forth rows.
3. \( D^{(3)} \) can still capture the persistent change idea even upon abnormal data points. Here the smoothing parameter \( k \) is selected arbitrarily, while it could be trained to an optimal value when we hope to use \( D^{(3)} \) as input features in regression models.