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The effect of foreign direct investment based on wireless network technology on China's regional economic growth

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Abstract

Foreign direct investment could not only provide funds to host countries, but also promote their economic growth. In view of this, research on the effect of foreign direct investment on the regional economic growth of China based on wireless network technology is studied. Firstly, the research on the sequence database was introduced. Secondly, the abnormal mining model based on incomplete data and the filling algorithm of mixed missing was introduced, with the filling effect analyzed. Finally, the algorithm was used, the results are analyzed, and the abnormal mining algorithm was improved. Through the example analysis, the data mining algorithm was used to predict the trend of China's regional economic development in the future.

Keywords: Foreign direct investment, Regional disparity, Capital formation, The trade effect

1 Introduction

Foreign direct investment (FDI) makes up for the host country funding gap and promotes employment, improving local human capital and introducing of technology and technology spillover way such as optimization of resource allocation efficiency of the host country to promote its economic growth [1]. Many studies have conducted an empirical study on the relationship between FDI and China's economic growth. The majority of the conclusion is that the large-scale inflow of foreign investment has provided great impetus for China's economic growth and the development of foreign trade [2]. Because China's reform and opening up is progressing gradually, the eastern region has attracted a lot of foreign direct investment with its geographical advantage, market size, and policy tilt. Moreover, the rapid development of regional economy and the rapid economic growth has further attracted more foreign direct investment. This creates a virtuous circle between foreign direct investment and regional economic growth. In the midwest and northeast, FDI is much lower than in the east. This has led to a huge increase in the imbalance between China's regional economic developments over

the past 30 years. For China's regions, FDI is an important source of funds for regional economic development. Its role is not only to solve the problem of lack of funds in regional economic development, but also to solve the indirect effects that come with it. And with the distribution of foreign direct investment in China, this kind of unbalance characteristics on the regional capital formation and economic growth, industrialization, and foreign trade and the influence of regional employment and technological innovation makes the very big difference [3]. Therefore, the research on the effect of foreign direct investment on regional economic growth in China is conducted based on wireless network technology.

2 State of the art

Nowadays, the world is an era of rapid information development, and the Internet has rapidly gained access to people's daily life. The wireless network with its quick, convenient, flexible, and efficient characteristics is closely related to people's lives [4]. With the wide application of 802.11g/b standard, the development trend of the new generation of wireless network is larger, faster, and wider. As a result, wireless access is coming, and the wireless network will have a bright tomorrow [4]. The wireless network supporting the communication between the computer technologies is wireless multiple access. This kind of wireless

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multi-access technology provides technical support for the mobility, personalized setting, and application of multimedia technology in daily communication [5]. Generally speaking, a wireless network is a computer network system that USES wireless transmission medium. A wireless network is a combination of wireless communication technology and computer network. At the same time, a wireless network is an important symbol of the vertical development of network technology in the twenty-first century [6]. The appearance of wireless network makes up for the shortage of wired network. With its own advantages, the wireless network has developed rapidly. The main features are as follows: reducing the impact of the environment on network laying: it is often very difficult to lay a wire network in the complex regional and urban complex. The emergence of wireless network simplifies network construction and thus expands the network area. Flexible network, quick economy: wired networks are difficult and inefficient for changing workplace and field operations, and building a wireless network is convenient for the economy [7].

3 Methodology

3.1 An overview of abnormal mining models based on incomplete data

It is distinguished from the traditional practice in the literature in this paper and generalized incomplete data of the missing model of matrix $Z = (Y, X)$ that the combination of matrix and response variables is missing. Mainly it is based on the following considerations: on the one hand, the existing literature is mostly the absence analysis of the matrix or response variables [8]. For example, some scholars have analyzed the individual deletion of the matrix, and the analysis of the multiplication estimation is carried out for the individual loss of response variable. On the other hand, the absence of matrix $Z = (Y, X)$ is more common in real data processing. The matrix X and the response variable Y are often incomplete [9]. The algorithm of matrix $Z = (Y, X)$ has universality, which can solve the single missing situation of matrix X and solve the individual deletion of response variable Y. It is more possible to solve the mixed missing condition of matrix X and response variable Y.

Therefore, in the first place, the EM algorithm and ML algorithm to deal with missing data are extended to the situation of mixed deletion, namely $Z = (Y, X)$. According to the deficiency of EM algorithm and ML algorithm, the RE algorithm is proposed according to the incomplete data filling theory of Weisberg. Then, the clustering analysis is carried out by the mining initial subset of the forward mining algorithm, and the conditional mean and covariance of the EM algorithm are simplified. In this way, we can excavate the initial subset

more quickly and obtain the improved forward mining algorithm with good effect. The research shows that the method of anomaly mining based on incomplete data is effective and feasible.

3.2 Mixed missing fill algorithm

The mixture of the missing filler algorithm consists of the EM algorithm, the ML algorithm, and the RE algorithm. The following are introduced in detail. For the EM algorithm, we set $Y = \chi\beta + \varepsilon = \beta_0 + X\beta_\Sigma + \varepsilon$, where Y is the $n \times 1$ response variable, and χ is the $n \times (p + 1)$ order matrix. The elements in the first column are all 1, and X is the matrix after the first column is removed from χ, $\beta = (\beta_1, \beta_2, \ldots, \beta_p)$ is the regression coefficient vector, and ε is the random error vector of $n \times 1$, and its distribution is $N(0, \sigma^2 I)$. There exists data deletion in the matrix $Z = (Y, X)$, that is, partial data of some variables is incomplete. In 1977, the algorithm proposed by Dempster, Larid, and Rubin as an iterative method which was widely used to deal with missing data problems. Each iteration of the EM algorithm consists of two steps: expected value (E step) and maximum value (M step). The missing pattern of the matrix $Z = (Y, X)$ is to create an EM algorithm like that. Let $Z = (Y, X)$ obey the multivariate normal distribution, namely:

$$Z_i(y_i, x_i) \sim N_P\left(\mu, \sum\right) \tag{1}$$

Among them:

$$\mu = \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \sum = \begin{pmatrix} \sum_{yy} & \sum_{yx} \\ \sum_{xy} & \sum_{xx} \end{pmatrix} \tag{2}$$

And in the matrix $Z = (Y, X)$, Z_{obs} is the known value, and the logarithmic maximum likelihood function of parameter $\theta = (\mu, \Sigma)$ is obtained in E steps:

$$\begin{aligned} Q\left(\theta/\theta^{(t-1)}\right) &= E\left[\log f(Z_{\mathrm{obs}}, Z_{\mathrm{mis}}/\theta)/Z_{\mathrm{obs}}, \theta^{(t-1)}\right] \\ &= \int_{Z_{\mathrm{mis}}} \log f(Z_{\mathrm{obs}}, Z_{\mathrm{mis}}/\theta) f\left(Z_{\mathrm{mis}}, Z_{\mathrm{obs}}/\theta^{(t-1)}\right) dZ_{\mathrm{mis}} \\ &= \int_{Z_{\mathrm{mis}}} \log f(X, Y/\theta) f\left(Z_{\mathrm{mis}}, Z_{\mathrm{obs}}/\theta^{(t-1)}\right) dZ_{\mathrm{mis}} \end{aligned} \tag{3}$$

where $\theta^{(t-1)}$ is the estimation of the parameter θ obtained by the $t - 1$ step iteration. $Q(\theta/\theta^{(t-1)})$ represents the logarithmic maximum likelihood function of parameter θ in $\theta^{(t-1)}$. So that is the conditional expectation of $\log f(Z_{\mathrm{obs}}, Z_{\mathrm{mis}}/\theta)$ in $\theta^{(t-1)}$ and Z_{obs}. $f(^*)$ is a probability distribution function. In the following M steps, the expectation function $Q(\theta/\theta^{(t-1)})$ is maximized to obtain the estimation $\theta^{(t)}$ of the parameter θ of the t step iteration.

$$\theta^{(t)} = \arg \max Q\left(\theta/\theta^{(t-1)}\right) \tag{4}$$

And then we use the new maximum value of $\theta^{(t)}$ to update the $\theta^{(t+1)}$ in the conditional prediction distribution. By (1)–(5.2), the estimation $\theta^{(t+1)}$ of the parameter θ of the $t+1$ step iteration is obtained. Repeat this algorithm until convergence. After convergence, we will converge θ as the estimate of parameter θ. As for the convergence of EM algorithm, there is a lot of literature on it. The following are the specific steps of EM algorithm for matrix Z = (Y, X): Because the EM algorithm is implemented by iterating and updating θ until convergence. Therefore, the key of the algorithm is to establish the relationship formula between $\theta^{(t-1)}$ and $\theta^{(t)}$. Let us start with $\theta^{(0)}$ as the initial value of $\theta = (\mu, \Sigma)$. Let us say $\hat{\mu}_{i,t}$ is the estimate of the ith element of μ that we get at step t. $\hat{\Sigma}_{j,k,t}$ is the estimated value of row j, column k, of Σ for step t. According to the formula of Atkinson and Cheng, the relationship formula between $\theta^{(t-1)}$ and $\theta^{(t)}$ is obtained (5)–(6). Where (5) and (6) are the estimates of μ and Σ in $\theta^{(t)}$ for the t step:

$$\hat{\mu}_{i,t} = \sum_{i=1}^{n} \hat{Z}_{ij,t-1}/n, \quad i = 1, \dots p \tag{5}$$

$$\Sigma_{j,k,t} = \sum_{i=1}^{n} \left\{ \left(\hat{Z}_{ij,t-1} - \hat{\mu}_{ij,t-1} \right) \left(\hat{Z}_{ik,t-1} - \hat{\mu}_{k,t-1} \right) + \hat{\Sigma}_{j,k,t-1} \right\}, i,$$
$$= 1, \dots p \tag{6}$$

Among them:

$$\hat{Z}_{ik,t-1} = E\left(Z_{ij}/Z_{\text{obs},i}, \theta^{(t-1)}\right) \quad Z_{ij} \text{ Unknown}$$
$$= Z_{ij} \quad Z_{ij} \text{ Known} \quad i = 1, \dots n, j = 1, \dots p \tag{7}$$

$$\hat{\Sigma}_{ik,t-1} = \text{cov}\left(Z_{ij}, Z_{ik}/Z \quad \theta^{(t-1)}\right) \quad Z_{ij}, Z_{ik} \text{ Unknown}$$
$$= 0 \quad Z_{ij} \text{ or } Z_{ik} \text{ Known} \quad i = 1, \dots n, j = 1, \dots p \tag{8}$$

Z_{obs} the known component of group I data. $\hat{Z}_{ij,t}$ is the value of the j column element in the ith row of the matrix Z obtained by iteration t. Z_{ij} is the value of column j of the ith row of the matrix Z. In formula (6), $\hat{\Sigma}_{ik,t}$ is the jth row, the k column element of the conditional covariance matrix $\hat{\Sigma}_{i,t-1}$ of group I data in the iteration of the $t-1$ step. For (7) and (8), if the conventional calculation method involves complex integral calculation, it is undoubtedly very tedious. In order to simplify the calculation, set y as the m dimension vector, y_1 as the p dimension component, y_2 as the q dimension component, $y \sim N(\mu, V)$, $V > 0$, where μ is mean, V is covariance matrix, and:

$$y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}, \mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, V = \begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix} \tag{9}$$

The conditional distribution of y_1 at a given y_2 is normal, and the conditional mean and conditional covariance are:

$$E(y_1/y_2) = \mu_1 + V_{11}V_{22}^{-1}(y_2 - \mu_2) \tag{10}$$

$$V(y_1/y_2) = V_1 - V_{11}V_{22}^{-1} \tag{11}$$

We apply the above results for each observed value of missing variables (i.e., each row of the matrix Z). So you just reorder the vectors of each row of the matrix Z, and you put the unknown quantity together as y_1 and the known quantity as y_2. The conditional expectation (7) and the conditional covariance (8) can be obtained by calculating the order of the elements in the mean μ and the conditional covariance. Set $Z_{i,t}$ as the ith row vector of the matrix Z at the tth iteration (i.e., the ith group observation). Rearrange the elements of $Z_{i,t}$ according to the missing condition of line I. Let Z_i^1 be the component of the unknown vector, and Z_i^2 as the component of known vector. After finishing, we get the following formula ($i = 1, \dots p$):

$$Z_{i,t} = \begin{pmatrix} Z_i^1 \\ Z_i^2 \end{pmatrix}, \mu_{i,t} = \begin{pmatrix} \mu_{i,t}^1 \\ \mu_{i,t}^2 \end{pmatrix}, \Sigma_{i,t}$$
$$= \begin{pmatrix} \Sigma_{i,t}^{11} & \Sigma_{i,t}^{12} \\ \Sigma_{i,t}^{21} & \Sigma_{i,t}^{22} \end{pmatrix} \tag{12}$$

where $\mu_{i,t}$ and $\Sigma_{i,t}$ are arranged in the order of the elements of Z_i^1 and Z_i^2, and the vectors obtained by the rearrangement of μ and Σ are obtained by iteration of step t. That is:

$$E\left(Z_i^1/Z_i^2\right) = \mu_{i,t}^1 + \Sigma_{i,t}^{12}\left(\Sigma_{i,t}^{22}\right)^{-1}\left(Z_{i,t}^2 - \mu_{i,t}^2\right) \tag{13}$$

$$\text{Cov}\left(Z_i^1/Z_i^2\right) = \mu_{i,t}^1 + \Sigma_{i,t}^{12}\left(\Sigma_{i,t}^{22}\right)^{-1}\Sigma_{i,t}^{21} \tag{14}$$

Then, the missing value will be filled into the matrix Z, and the covariance will be rearranged in order of the original columns. The advantage of (13) and (14) is that the missing value of a set of data can be estimated rapidly each time, which is better than (7) and (8); only one missing value is estimated at a time, and the calculation is simple. Iterative calculation is (5), (6), (13), (14), and until $\theta^{(t)}$ converges. In the case of convergence, we fill the matrix with the estimated value. The conditional covariance matrix of group i data is also represented by $\hat{C}$. The regression parameters β and s^2 are obtained by the following transformation:

$$\hat{\beta}_{\Sigma} = \hat{\Sigma}_{xx}^{-1}\hat{\Sigma}_{xy}, \hat{\beta}_0 = \hat{\mu}-\hat{\beta}_{\Sigma}^T\hat{\mu}_x, \hat{\sigma}_2 = \sigma_y^2-\hat{\Sigma}_{yx}\hat{\Sigma}_{xx}^{-1}\hat{\Sigma}_{xy} \quad (15)$$

For ML algorithm, we can also extend Atkinson's ML algorithm to the mixed missing mode, namely the missing mode of matrix $Z = (Y, X)$. Set Z_{obs} as the set of the known values, Z_{mis} as the collection of missing values, and the posterior density of total Q can be written as follows:

$$h(Q|Z_{\text{obs}}) = \int g(Q|Z_{\text{obs}}, Z_{\text{mis}})f(Z_{\text{mis}}|Z_{\text{obs}})dZ_{\text{mis}} \tag{16}$$

where $f(\cdot)$ is the posterior density of the missing value. $g(\cdot)$ is the posterior density of the complete data of. According to previous literatures, it is easy to obtain the following formula (replace Y with $\hat{Y}$):

$$b_t = \left(\hat{\chi}_l^T\hat{\chi}_t\right)^{-1}\hat{\chi}\hat{Y}, l = 1,...s, \overline{b} = \sum_{l=1}^{s} b_l/s, \tag{17}$$

$$U = \sum_{l=1}^{s} \hat{\sigma}_{yl}^2\left(\hat{\chi}_l^T\hat{\chi}_t\right)^{-1}/s, B$$
$$= \left(b_l-\overline{b}\right)\left(b_l-\overline{b}\right)^T/(s-1), \text{ var}\left(\overline{b}\right)$$
$$= U + \frac{s+1}{s}B. \tag{18}$$

In order to obtain the estimated parameters and (17), the covariance estimation of the parameters can be obtained through Eq. (16). The biggest disadvantage of EM algorithm and ML algorithm is that the algorithm relies on the specific distribution of observed values. According to the incomplete data filling theory of Weisberg, we proposed that the RE algorithm still considers the mixed missing situation. Here are the specific algorithm steps: let us say $Z_i = (Z_{\text{obs}, i}, Z_{\text{mis}, i}), Z_i$ is the ith row vector of matrix Z. $Z_{\text{obs}, i}$ is the component of the reconstituted component of the known value. $Z_{\text{mis}, i}$ is the component of the unknown value. Search for missing values by row vectors and find the most relevant points. Set $Z_{i, j}$ as the

missing element of the ith row j column of search to matrix Z. Then, we look for point $Z_{i, k}$. Content:

$$R\left(Z_{i,k}, Z_{i,j}\right) = \max_{Z_{i,l}\in Z_{obsi}} R\left(Z_{i,l}, Z_{i,j}\right) \tag{19}$$

where $R(Z_{i, k}, Z_{i, j})$ is the correlation coefficient of the k and j columns in matrix Z. It is generally assumed that $R(Z_{i, k}, Z_{i, j})$ is better than 0.5. Establish the linear equation between the k column and the j column:

$$L_j = \beta_0 + L_K\beta_1 \tag{20}$$

L_j is the j column element, and L_K is the k column element. (β_0, β_1) is the estimated parameter. According to the regression equation and the known value $Z_{i, k}$, we get the estimate of $Z_{i, j}$. In this way, repeat the above steps to fill in the other missing values, until the filling is complete. To get the whole matrix. Then we compare the actual effect of four methods: EM algorithm, ML algorithm, RE algorithm, and variable. The matrix X is generated from the multiple normal distribution $N(O, I_p)$, $p = 5$. The regression coefficient is $(\beta_0, \beta_1, \beta_2, \beta_3, \beta_4)$ = (4, 6, 8, 10) and $\varepsilon_i \sim N(0, 0.5I_p)$. The matrix Y is obtained by the linear model, and the matrix $Z = (Y, X)$ is obtained. The sample size is $n = 50$ and 100 respectively, and we randomly generate two sets of data. Then, the elements of 10%, 20%, 30%, and 40% of the matrix Z are randomly missing, and the parameters and real values obtained by various algorithms are compared. In order to better compare the effect, we give the median estimate used by Atkinson. On the filling of mixed missing data, the EM algorithm is undoubtedly the best, and the ML algorithm is better in the estimation times. Through computer simulation, we believe that the ML algorithm can achieve better results after 10 steps. Too many times, because the increase in the estimation error may reduce the estimation effect, it is easy to see that in the above algorithm, the median estimation method is the least accurate. Although the RE algorithm is not as
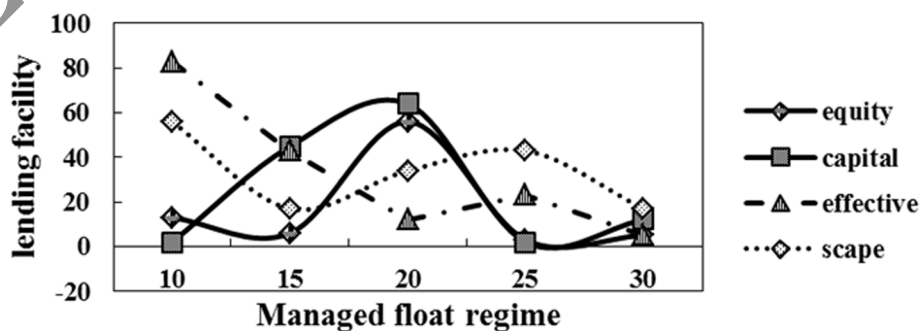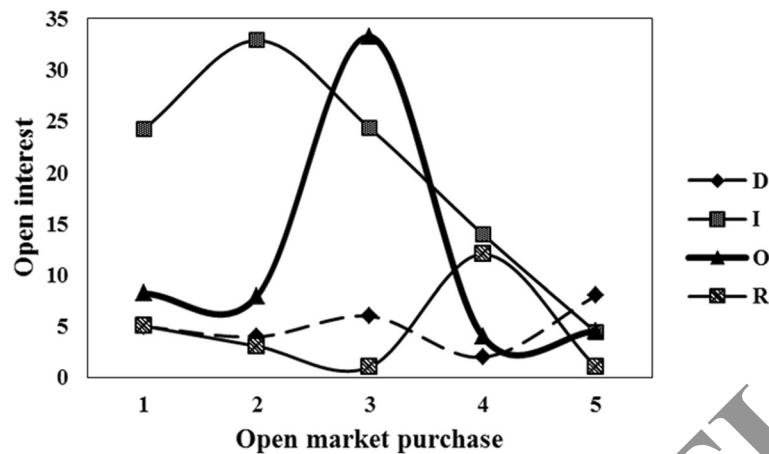

Fig. 1 1–30th observation studentized residual figure

Fig. 2 22nd observation studentized residual figure

effective as the EM algorithm, it is easy to perform and better than the median estimate.

4 Result analysis and discussion

4.1 The example analysis

Considering the lack of the mixture, that is, the absence of matrix $Z = (Y, X)$, the random deletion of 10% of the data are studied in the previous literatures. When searching the initial subset, the variance is estimated as $\hat{\sigma}_q^2 = 3.1421e{-}004$. Figures 1 and 2 are all 30 observation points, 1–28 observation points, and 22 observation points in the search for each step of the student's residual error:

It can be seen from the figure that the student residuals of the 29 and 30 observation values are far away from (– 2, 2). In the 1–28 observation points, except for the twenty-second observation point, it is strictly between (– 2, 2). When the search subset reaches 29, the residual cluster produces an obvious "shoot." This is because the subsets enter the outliers. From the position of "scattering," the number of abnormal points can be determined. The following results are obtained by regression. The following Table 1 shows (/= 29, 30).

According to $F(l) \approx 14.5123 > F_{0.95}$ and (2, 30–3–2) = 3.39, and R_I is larger, it is obvious that the observation values of 29 and 30 are abnormal points. This is consistent with the results obtained by Atkinson and Cheng.

4.2 Improvement of an abnormal mining algorithm

When the initial subset is excavated, cluster analysis is applied to classify the observation points into several classes as objects for the mining of forward mining algorithms. Thus, a comprehensive search result can be achieved with very few searches. If the observed value contained in a class is less than or equal to the initial subset number p, then all the selected points are selected from each class. If the observed value in a class is greater than the initial subset number p, then a point can be selected randomly from each class. In this way, the number of representative point s, which is $s < m \, p < n$ (since, in most cases, s is significantly less than n. Therefore, it is possible to combine clustering with forward search to simplify the initial subset of search). The new design matrix X and Y are formed according to the selected points, and the forward mining algorithm is used to find the initial subset. The results below show that the improved results are surprisingly good. According to the 100 data cited by Andrzej and Kosinski, the first 60 observation points are the "good" data observation points that we need for the regression, and the mean value is the binary normal distribution of $\mu_1 = \mu_2 = 0; \sigma_1^2 = \sigma_2^2 = 40; \rho = 0.7$. The last 40 observation points are the "bad" view points of the regression, which are the abnormal points, which are the binary normal distribution of $\mu_1 = 18, \mu_2 = -18; \sigma_1^2 = \sigma_2^2 = 1; \rho = 0$. Its results are shown in the following Table 2: Among them, without clustering, 1 = 1–60; 1 = 61–100 after clustering.

Figure 3 shows the residual and regression images obtained after 1000 searches without cluster analysis. It also show that graph of the total student's map of 100 observations, the student's map of the first 60 observation points, the student's map of the last 40 observation points,

Table 1 Parameter estimate and testing

β_0	β_1	β_2	$F(l)$	R_1
l.7489	0.5097	– 0.2959	14.5123	0.2197

Table 2 Contrast of parameter estimate and testing

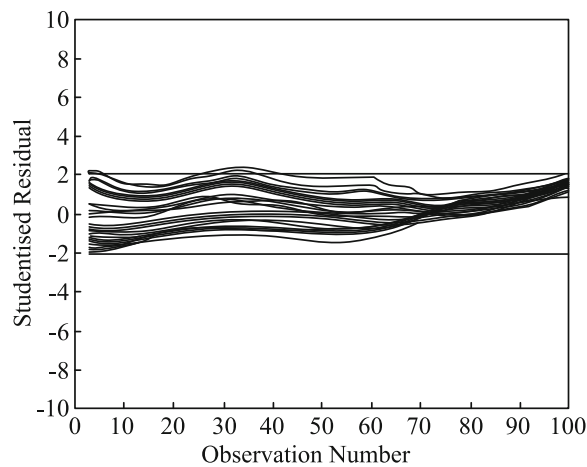|	β_0	β_1	$F(l)$	R_1
Before clustering	2.0863	– 0.8767	10.762	0.0238
After clustering	0.2099	0.7908	120.34	0.9762

Fig. 3 60–100th observation studentized residual figure

and the regression scheme of all the data. According to the judgment, the first 60 observation points are the wrong conclusions of the observation points.

Figures 3 and 4 are obtained after applying cluster analysis. From the figure, it can be seen that the first 60 observation points after the application clustering analysis are good observation points and then 40 points are the correct conclusion of the anomaly points. Moreover, the students of the first 60 points had the scattering phenomenon after the observation subset number exceeded 60. The number of abnormal points can also be determined by this chart. Look at both $F(I)$ and R_I, although both $F(I)$ is greater than $F_{0.95}(40, 100 - 40 - 2) \approx 1.58$. But when $I = 61{-}100$, $F(I)$ is bigger and $R_I = 0.9762$ is closer to 1. In general, 40 points after V are abnormal. Through the above improvement, it can be seen that the combination of clustering analysis and forward mining algorithm produces ideal anomaly mining results. This is exactly what the forward mining algorithm cannot achieve. Such improvements can also save a lot of
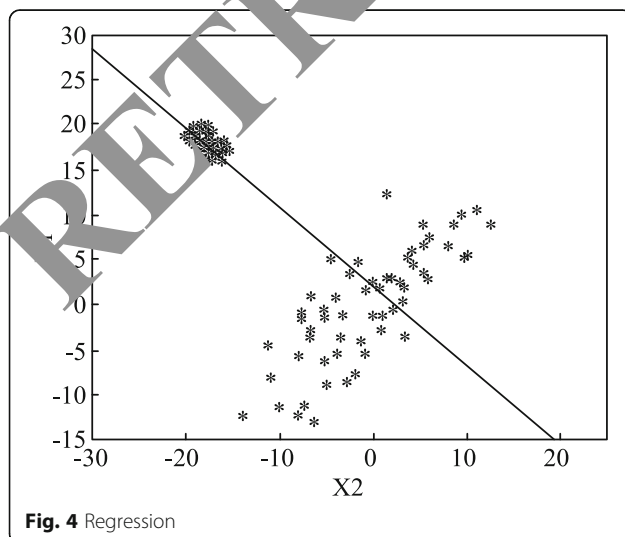

Fig. 4 Regression

time for exceptional mining, which is particularly important in large databases. In conclusion, this paper generalizes the existing methods of the literature to the situation of mixed deletion, studies various filling algorithms, proposes the RE algorithm, and compares the filling effect with the simulated method. The conclusion is very encouraging. In this paper, the process of forward mining algorithm is improved.

5 Conclusion

Foreign direct investment had a positive impact on employment in China, especially the labor-intensive industries with foreign investment which have made a greater contribution to China's employment. According to the study, due to the "dual" characteristics of China's economy, the underdeveloped midwestern hinterland needs more capital of various abilities. Therefore, what China needs to do in the future is to attract FDI to the central and western regions and northeastern China. The study is based on statistical analysis, which is why we have chosen to rely on the statistical techniques in the data mining in the field of statistical techniques—the series excavation and the anomaly excavation, the clustering and the visualization, the missing data and the interpolation, the risk and the prediction, and so on. The studies herein are based on a linear regression model. And introducing the abnormal mining model based on incomplete data, finding that the incomplete data mining algorithm could estimate the abnormal and the actual value is very close to the lack of outliers which can unearth them and can be used to analyze the regional economy. And in this case, the filler algorithm that is going to be talked about is going to reduce the error value of the data. In particular, the prediction accuracy can be further improved by two-step prediction and the modified algorithm based on anomaly mining.

Author's contributions
HYZ made a great contribution to the FDI of wireless network technology. The author read and approved the final manuscript.

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HY Z, Master of Economics, Associate professor. Graduated from Hunan University in 2006. Working in Shaoyang University. He research interests include Regional economy and low carbon economy.

Competing interests
The author declares no competing interests.

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