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Research on Urban Resource Allocation Based on Support Vector Machines

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Abstract: In this paper, a semi-supervised quadratic support vector model is used to classify the level of high-quality economic development of 296 cities in China. Then, the amount of resource allocation required for cities to achieve high-quality economic development under resource constraints is calculated based on the classification hyperplane determined by the model. The article proposes development suggestions for resource allocation in terms of labour, land, fixed assets, energy, finance, healthcare, transportation, education, social security, environment and openness.

1. Introduction

Dornbusch (2011) [1]defines the concept of economic growth as:- "the result of improved factor accumulation and resource utilization or increased factor productivity." .Kamaev(1983)[2] pointed out that it is not enough to analyse the problem of economic growth solely in terms of the quantity of economic growth, but that the problem of economic growth also depends on the efficiency of the use of productive and unproductive resources. Economic growth is essentially a reflection of the relationship between resource factor inputs and final output. The Nineteenth National Congress of the Communist Party of China put forward for the first time a new formulation of high-quality development, which calls for greater attention to efficiency and effectiveness in resource allocation and ensures the rational allocation and optimal use of resources. Through rational resource allocation, production efficiency and output quality can be improved, promoting the efficient development of the economy. High-quality development should be based on the improvement of factors of production, productivity and total factor efficiency, rather than on the expansion of the volume of factor inputs.

2. Literature review

The concept of resources or factors is differentiated in economics between a narrow and a broad sense. The former refers to natural resources such as land, water and mineral deposits. The latter refers to the inclusion of natural and social resources. Adam Smith(2016)[3] emphasised the division of labour and capital accumulation as the main drivers of economic growth, rejecting the agrarian view of landed produce as the only source of increased wealth and suggesting the importance of labour. The theory of economic growth proposed by Malthus,(2018)[4] on the other hand, emphasised the importance of the factor of population growth in economic growth. Schumpeter(1983)[5] introduced the concept of innovation and explored its role in the process of economic growth. Classical economists were the first to explore the determinants affecting economic growth and developed a basic consensus on the role of factors such as capital and labour. The Harold-Dormer model explains the relationship between investment, savings and economic growth, but at the same time overemphasizes the decisive role of capital accumulation and fails to consider the role of technological progress in economic growth. The model proposed by Solow effectively measures the degree of contribution of each factor to economic growth, and many subsequent econometric models have been constructed using the analytical method of the model as their theoretical basis.

The scarcity of resources determines that the optimal allocation of resources is a fundamental issue in economics. Resource allocation usually refers to how limited human, material and financial resources, as well as scientific, technological and information resources, can be channelled to different regions, sectors and enterprises in order to maximize output, given a certain amount of resources. In other words, resource allocation refers to the selection of relatively scarce resources after comparing them with different uses according to the needs of society. In the process of modern economic operation, there are two ways of resource allocation and reallocation: the market way and the planning way. These two ways of resource allocation are different in nature. Market allocation of resources is a natural process, the advantages and disadvantages of which are basically determined by objective factors (internal mechanism). The planned allocation of resources is a man-made process, and its advantages and disadvantages are basically determined by subjective factors (external forces). Hong Yinxing (2014) [6]made a theoretical study on the role of government after the market plays a decisive role in resource allocation in China. He believes that in distinguishing the boundary between the role of the government and the market can not be assumed that a strong market is necessarily a weak government. As long as the two are not acting in the same field of resource allocation and at the same level, the government and the market will not be in conflict.

When resource mismatch occurs, it will bring negative impacts. Hsieh and Klenow(2009)[7] established the transmission mechanism of resource mismatch to the total factor productivity impairment of the aggregate industry, which provides the economic theory foundation from micro to macro for the study of resource mismatch. On the basis of their research, more scholars joined in the study of resource mismatch. Gai Qing'en (2011) et al[8]. Theoretically illustrate the mechanism of the impact of land resource misallocation on China's plus total labour productivity, and evaluate the extent of the impact of land resource misallocation based on detailed microdata. Gong Guan (2018) et al[9]. use microdata on China's manufacturing sector from 1998-2007 to demonstrate that if both capital and labour were efficiently allocated, China's total factor productivity in the manufacturing sector would have increased by 57.1% in 1998 and by 30.1% in 2007.

Some scholars determine the optimal allocation of resources by building models. Yang Xiutai(1993)[10] constructed a mathematical model of the optimal allocation of socialist resources, and deduced the measurement standard of the optimal allocation of socialist resources, that is, if the resources reach the Pareto optimal allocation state under the condition of distribution by labour, then the optimal allocation of resources is achieved. It is believed that the optimal allocation of resources is achieved when resources reach the Pareto optimal allocation state under the condition of distribution according to labour, otherwise, the optimal allocation of resources is not achieved. Chen Heben(1993)[11] deduced the optimal allocation formula when two factors of production are allocated to n interrelated production sectors from some basic assumptions. Yin Kedong(2012)[12] established a multi-objective linear programming conformity model for optimal control of resource allocation. Jiang Tao (2002)[13] established a multi-objective optimal planning model for sustainable development based on the dynamic input-output principle to analyse and simulate China's medium- and long-term sustainable development on the basis of qualitative analysis. With the help of game theory, Zhang Yishan(2009)[14] mathematically prove that in order to achieve the optimal allocation of resources and optimise social interests and welfare, it is necessary to require the power of different economic agents within the same level to be equal, and at the same time to ensure the symmetry of the power and responsibility of each economic agent.

Many economists agree that machine learning will have a broad and far-reaching impact on the development of economics. In the near future, machine learning will change the way economics is studied. Susan Athey(2018), the first female Clark Prize winner and a professor at Stanford University, believes that machine learning (ML) will have a huge impact on the development of economics[15]. She believes that machine learning acts on the economics research paradigm through two main mechanisms: supervised learning and unsupervised learning. This standardised model selection will have profound implications for empirical research in economics, where researchers are also often faced with covariate selection and model selection problems. Despite its many technological advances, machine learning faces problems that are inconsistent with traditional methodologies for causal inference in econometrics. Kleinberg, and Mullainathan (2017) [16]of Harvard University, along with a number of other researchers, have argued that existing machine learning algorithms are still inadequate for estimating and calibrating forecasting models for economic policy. They are not capable of carrying out this "forecasting" task for the implementation of important economic policies. However, there have been attempts to use machine learning to predict the economy. Li Lingling(2015)[17] used particle swarm support vector machine and fuzzy regression methods to provide early warning of annual and monthly boom indices of economic cycles based on the characterization of economic cycle fluctuations. Zhou Zi-Ying (2011)[18] et al. proposed a regional economic forecasting model (PCA-SVM) based on support vector machine with principal component analysis. Liu Guangli(2003) [19] combined support vector machine, fuzzy theory and macroeconomic early warning research, tried to establish a macroeconomic early warning method system based on support vector machine, and broadened the theory and method of support vector machine. Existing research strongly supports the feasibility of applying machine learning methods in macroeconomic research, and its shortcoming is that it is unable to achieve the guidance of effective resource allocation through this prediction. In this study, we will take the city as the research object and calculate the resource allocation results required for the city to achieve high-quality development at the macro level by building a non-kernel support vector machine.

3. Research Design

3.1. Model Construction

Support vector machine is essentially a classifier, using sample data to find a hyperplane to achieve classification prediction of out-of-sample data after training the model. Since most of the data sets are non-linearly separable in space, kernel functions are usually introduced to deal with them. However, this treatment does not allow to obtain an explicit expression for the classification hyperplane function, which cannot be used for subsequent prediction of resource allocation paths.

The quadratic surface support vector machine (QSSVM) method proposed by Luo (2014)[20] can express the classification hyperplane explicitly. We use it as a base model for constructing high-quality developmental classification.QSSVM is trained to obtain the parameter set (W,b,c) of the model's quadratic surface $g(x) \triangleq \frac{1}{2}x^T W x + b^T x + c = 0$ based on a dataset $\{(x_i, y_i)_{i=1}^{l}\}$, where $x_i = \left(x_i^1, x_i^2, \cdots, x_i^m\right)^T \in \mathbb{R}^m$, $y_i \in \{1, -1\}, i = 1, \cdots, l$, $W = \left(w_{ij}\right)_{m \times m} \in \mathbb{S}^m$, $b = \left(b_i\right)_m \in \mathbb{R}^m$. The quadratic surface is capable of appropriately binary classifying the individual training points $\{x_i\}_{i=1}^{l}$ according to their corresponding labels. Luo (2017) transformed QSSVM into a minimization problem by maximizing the sum of the relative geometric distances from each training point to the hyperplane $g(x) = 0$ as well as minimizing the classification error of all training points.

$$
\begin{aligned}
&(\text{QSSVM}) \min_{\boldsymbol{W} \in \mathbb{S}^m, \boldsymbol{b} \in \mathbb{R}^m, c \in \mathbb{R}, \xi \in \mathbb{R}^l} \sum_{i=1}^{l} \left\| \boldsymbol{W} \boldsymbol{x}^i + \boldsymbol{b} \right\|_2^2 + C_l \sum_{i=1}^{l} \xi_i \\
&\text{s.t.}\, y_i \left(\frac{1}{2} \left(\boldsymbol{x}^i\right)^T \boldsymbol{W} \boldsymbol{x}^i + \boldsymbol{b}^T \boldsymbol{x}^i + c \right) \geqslant 1 - \xi_i, i = 1, \ldots, l \\
&\boldsymbol{\xi} = (\xi_1, \xi_2, \ldots, \xi_l)^T \geqslant 0
\end{aligned} \tag{1}
$$

where the slack variable ξ_i is the marginal distance of classification error of x_i, and $C_l > 0$ is the penalty coefficient. Luo (2014) did not use the kernel function approach for the solution, but rather transformed the problem in the original space, which in turn transformed the problem into a convex quadratic programming problem with linear constraints.

Sometimes not all training data points can be labeled, or the cost of labeling all training data points is too high. Machine learning where only some of the data points are labeled is called semi-supervised learning. On the basis of QSSVM, Yan (2016)[21] et al. proposed Semi-supervised quadratic surface support vector machine (SSQSSVM), which utilizes a semi-positive definite relaxation approach to solve the model, and the details of the solution process can be found in their literature. The model will be used in this study and applied to the field of optimal resource allocation.

Except for the studied cities (Foshan City is chosen in this paper), the main resource input vector $X_i = \left(x_i^1, x_i^2, \cdots\cdots, x_i^m\right)$ for each city i is used to train the model, where m is the number of resource types and $i = 1, 2 \cdots, n$. At the same time, the cities with high quality development are marked with positive label $y_i = 1$, and the cities with lagging quality are marked with negative label $y_i = -1$. The number of data points with labels is l, and the rest of $n - l$ cities are not marked with labels. 30% of the positively and negatively labelled data points in the labeled dataset are randomly selected to be used for the training of the SSQSSVM model along with all $n - l$ unlabeled data points. The remaining 70% of positively and negatively labeled data points are used to test the model. The ultimate goal is to find hyperplane in space that can reasonably classify the data points.

Based on the quadratic surface function obtained above, the classification of the out-of-sample point can be obtained and the optimal path of the point away from (when in positive class) or to (when in negative class) the quadratic surface can be calculated based on the classification, and (assuming negative class) its projected point on the surface is the projected number of resource allocation without constraints. In reality, resources are scarce and partially rigid, so further discussion of resource allocation predictors under resource conditions with constraints is needed.

3.2. Selection of variables

Resources in a broad sense include: natural, socio-economic and technological resources.

Socio-economic resources are social and economic factors that directly or indirectly contribute to production. Among them, population and labour force are the main conditions for socio-economic development. Technological resources play an increasingly important role in economic development. Technology is the application of natural science knowledge in the production process and is a direct productive force. Resources include, but are not limited to: labour, land, fixed assets, energy, finance, finance, health care, education, transportation, information, technology, etc.

On the basis of the three classifications of resources, resources are further subdivided. The following indicators are selected to represent the corresponding resource inputs, respectively, as shown in Table 1.

Table 1: Classifications of resources.

Resource categories	Resource subcategories	Resource indicators
Natural resources	Land	Land area of built-up area
	Energy	Industrial Electricity
Socio-economic resources	Labour	Number of employees in manufacturing industry
		Number of students enrolled in general undergraduate colleges and universities
	Government Expenditure	General Public Budget Expenditure
		Expenditure on Education
		Science and Technology Expenditure
	Financial and Investment	Fixed Asset Investment
		Amount of actual foreign investment
		Year-end balance of loans from financial institutions
	Medical resources	Number of hospital beds
		Number of licensed or assistant doctors
	Public resources	Public library collection
		Publicly operated motorcycles at the end of the year
	Transportation	Road freight volume
		Civil air cargo volume
		Miles of urban rail transport in operation
		Road mileage
		Highway mileage
	Social Security Resources	Number of urban workers' basic pension insurance participants
		Number of urban workers enrolled in medical insurance
		Number of urban workers covered by unemployment insurance
	Environmental security	Comprehensive utilisation rate of industrial solid waste
		Green coverage area of built-up areas
Technical resources	Information resources	Number of mobile phone subscribers at the end of the year
		Number of Internet broadband access users

3.3. Data pre-processing

The sample data are selected from the 2019 Municipal Statistical Yearbook data of 296 prefecture-level cities across China and the 2019 China Urban Statistical Yearbook. The data are taken from CEIC Macroeconomic Database and National Research Network. Due to missing data for 2019, 2018 statistics were used for four variables: fixed asset investment, foreign real investment, road mileage, and highway mileage. For the treatment of missing data of individual cities and municipalities in each variable, the project adopts the k-nearest neighbours algorithm (KNN). The data points missing a feature attribute are found to be the nearest K points in space through the categorisation method, and the average value of this feature attribute of these K points is used as the corresponding fill value of the point. In this study the K value is set to 6.

Descriptive statistics for each variable for the 296 cities are shown in Table 2.

Table 2: Results of descriptive statistics

Resource indicators	Mean	Max	Min	Median	Standard Variance
Land area of built-up area (square kilometre)	158	1497	0.7	89	211
Industrial Electricity	1406227	12277696	10215	874196	1595849
Number of employees in manufacturing industry (person)	145147	2218756	240	59417	265077
Number of students enrolled in general undergraduate colleges and universities (person)	97665	1086407	1214	36282	173776
General Public Budget Expenditure (ten thousand yuan)	5176033	83515363	325543	3481798	7839436
Expenditure on Education(ten thousand yuan)	840743	10255068	49846	606461	1052935
Science and Technology Expenditure(ten thousand yuan)	155754	5549817	918	38165	510960
Fixed Asset Investment (million)	199493	1744057	5949.89	149100	199355
Amount of actual foreign investment(ten thousand dollars)	96507	1731089	15	23566	216255
Year-end balance of loans from financial institutions (ten thousand yuan)	41887015	7.05E+08	1250767	15235454	84252104
Number of hospital beds (bed)	20909	162147	785	15981	20011
Number of licensed or assistant doctors (person)	11624	109376	451	8261	11954
Public library collection (ten thousand copies)	339	7894	2	156	710
Publicly operated motorcycles at the end of the year	1765	38728	7	705	3510
Road freight volume (tonnes)	12832	107064	142	10041	11925
Civil air cargo volume (tonnes)	51716	4175700	0	4	299887
Miles of urban rail transport in operation (Kilometer)	17	679	0	0	74
Road mileage	14181	147881	988	12648	12180
Highway mileage(Kilometer)	415	3119	0	360	321
Number of urban workers' basic pension insurance participants (person)	1152207	15914979	11899	655446	1864880
Number of urban workers enrolled in medical insurance (person)	1101437	33712821	29022	500622	2631870
Number of urban workers covered by unemployment insurance (person)	629052	12407013	11281	270417	1335970
Comprehensive utilisation rate of industrial solid waste (percent)	73	100	0.21	79	23
Green coverage area of built-up areas (hectares)	8402	147048	150	4168	16099
Number of mobile phone subscribers at the end of the year (10,000 households)	514	4009	15	369	562
Number of Internet broadband access users (10,000 households)	136	1274	1	97	140

3.4. Feature selection

Not all features are equally important for final classification. Keeping the more informative features and discarding the less informative ones through feature selection helps to improve the efficiency of training. If two features in the feature matrix have high correlation then they contain very similar information. Therefore, the correlation matrix is used to check for the presence of features with high correlation and if present, one of them is removed. The correlation coefficient was set to 0.9 and the remaining 14 features after calculating the correlation matrix and processing are shown in Table 3.

Table 3: Resource indicators after feature selection

Resource indicators	
Land area of built-up area (square kilometre)	Number of hospital beds (bed)
Industrial Electricity	Road freight volume (tonnes)
Number of employees in manufacturing industry (person)	Civil air cargo volume (tonnes)
Number of students enrolled in general undergraduate colleges and universities (person)	Road mileage
General Public Budget Expenditure (ten thousand yuan)	Highway mileage(Kilometer)
Fixed Asset Investment (million)	Number of urban workers enrolled in medical insurance (person)
Amount of actual foreign investment(ten thousand dollars)	Comprehensive utilisation rate of industrial solid waste (percent)

3.5. Model training

The 296 cities in China are used as the study sample point set $\boldsymbol{X} = \left\{x_1,\cdots,x_n\right\}$, where $.n = 1,2,\cdots,296$. The input feature vector $\left(x_i^1,\cdots,x_i^{14}\right)$ consists of its 14 resource indicators. Some of the cities are labelled. Among them, the positive category labels are based on the 2019 Advanced Manufacturing City Development Index published by SEDI Consultants, and the top 15 cities are selected to be labelled as positive labels after excluding Foshan City. As the report only ranks the top 50 cities in the Advanced Manufacturing City Development Index. For the labelling of negative labels, we assume that the development level of manufacturing industries with fewer manufacturing employees is correspondingly lower. Therefore, the bottom 15 cities in terms of manufacturing employees are labelled as negative labels. The remaining 266 cities are not labelled, and the corresponding labels are given by the trained model. A semi-supervised learning problem is constructed (e.g., Table 4).

Table 4: Positive and negative class labelled cities before model training

City	Label	City	Label
Qitaihe	Negative	Shanghai	Positive
Sanya	Negative	Beijing	Positive
Yichun	Negative	Nanjing	Positive
Danzhou	Negative	Xiamen	Positive
Jiayuguan	Negative	Hefei	Positive
Guyuan	Negative	Tianjin	Positive
Shannan	Negative	Ningbo	Positive
Pingliang	Negative	Guangzhou	Positive
Lhasa	Negative	Chengdu	Positive
Rikaze	Negative	Hangzhou	Positive
Changdu	Negative	Wuhan	Positive
Linzhi	Negative	Qingdao	Positive
Haidong	Negative	Shenzhen	Positive
Nagchu	Negativ	Suzhou	Positive
Longnan	Negativ	Chongqing	Positive

To prevent model overfitting, 30% of the labelled city samples were used as the training set and the remaining 70% as the test set. The model that minimises the Mean Absolute Error (MAE) of the test set is selected as the final model. The selection of penalty parameters in the model is done by grid search and the setting interval is.$[2^{-2},2^2]$.

4. Conclusion

The output obtained after inputting the relevant data of Foshan City in 2019 into the model is a positive class label, which is consistent with the conclusions of the 2019 Advanced Manufacturing City Development Index published by SEDI Consultants.

Using the classification hyperplane identified by the model, the resource allocation required for Foshan City to further seek to improve the level of high-quality development of the manufacturing industry is obtained by calculating the projection points on the hyperplane at a higher level. As most of the resource inputs are rigid over a period of time, such as public expenditures, or difficult to achieve large-scale changes in a short period of time, such as infrastructure construction. Therefore, when calculating the projection point, we set upper and lower limits on the input of resources, the lower limit is 0.9, that is, the reduction of the input of resources can not be less than 0,9 times of the existing resources, and the upper limit is set to 1.5, that is, the increase of the input of resources can not be more than 1.5 times of the existing resources. It is worth noting that, when the above conditions are imposed on all the resources, the model can not find the optimal solution, which means that some of the resources need to be more. Therefore, a recursive approach is used to filter resources for which upper and lower limits can be set while ensuring that there is an optimal solution. And because there is substitutability between resources, the result of this combination of resources is not unique. One of the combinations is that the optimal solution can be found when no upper limit is set for the three indicators of general undergraduate students, the number of urban workers' basic medical insurance participants, and road mileage, reflecting the prominent role of these three resources. Under this setting, the before-and-after allocation of each resource changes as follows (e.g., Table 5):

Table 5: Before and after comparison of the volume of resources

Resource indicators	Current value	Aim value	Change in value
Number of employees in manufacturing industry (person)	1070486	963437	-
Land area of built-up area (square kilometre)	161	241.498	+
Fixed Asset Investment (million)	426579.2	639869	+
Amount of actual foreign investment(ten thousand dollars)	147950.7	133156	-
General Public Budget Expenditure (ten thousand yuan)	8065443	7554330	+
Number of students enrolled in general undergraduate colleges and universities (person)	123575	2989400	-
Number of hospital beds (bed)	34508	51762	+
Road mileage	27487	24738.3	-
Highway mileage(Kilometer)	459	688.5	+
Industrial Electricity	4488564	4039710	-
Comprehensive utilisation rate of industrial solid waste (percent)	82.87	100	+
Number of urban workers enrolled in medical insurance (person)	3246530	13527000	+
Road mileage	5366	590887	+
Highway mileage(Kilometer)	487	438.3	-

The value of change reveals that the demand for manufacturing population has decreased under the high quality development of manufacturing in the city. Machines will replace human labour more in the manufacturing process in the future. This will become more prominent when automation, informationization and intelligent production become more widespread. The steady decline in real foreign investment, local general public budget expenditures, road freight, and industrial electricity consumption reflects a more rational and optimal use of the internal structure of resources. Rather than relying solely on quantitative inputs, it also reflects the fact that cities will tend to be green, energy-saving and environmentally friendly in the future.

The most obvious growth is in the three indicators of the number of students enrolled in general undergraduate and tertiary programmes, the number of urban workers enrolled in basic medical insurance, and the mileage of roads. Firstly, combining the decrease in the manufacturing population with the increase in the demand for resources for general undergraduate and tertiary students, it is not difficult to find that it is the high-quality manufacturing industry that has a clear requirement for the structuring of the workforce. There is a greater demand for highly skilled personnel to engage in the manufacturing industry and to enhance the development of the manufacturing industry from the perspective of the labour force. Secondly, it is the growth of the number of urban workers' basic medical insurance participants, and the improvement of basic medical insurance plays an important role in the survival of the labour force in the manufacturing industry. Thirdly, the growth of road mileage plays an important role in the development of the supply chain and logistics of the manufacturing industry, and in the exchange of personnel between enterprises, especially as there is generally a clustering effect in the manufacturing industry, and the construction of roads helps to form a convenient traffic circle between neighbouring cities.

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