COVID-19 In Shang Hai: It is Worth Learning from the Successful Experience in Preventing and Controlling the Overseas Epidemic Situation

Qi Dang

Macau University of Science and Technology

Rui Miao

Macau University of Science and Technology

Liang Yong (✉ yongliangresearch@gmail.com)

Macau University of Science and Technology

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COVID-19 In Shang Hai: It is Worth Learning from the Successful Experience in Preventing and Controlling the Overseas Epidemic Situation

Qi Dang¹, Rui Miao¹, Yong Liang^{1,2,3*}

Abstract

Background

COVID-19 first appeared in Wuhan, Hubei Province, China in late December 2019 and spread rapidly in China. Currently, the spread of local epidemics has been basically blocked. The import of overseas epidemics has become the main form of growth in China's new epidemic. As an important international transportation hub in China, Shanghai is one of the regions with the highest risk of imported cases abroad. Due to imported overseas cases are affected by the international epidemic trend. The traditional infectious disease model is difficult to accurately predict the cumulative trend of cumulative cases in the Shanghai areas. It is also difficult to accurately evaluate the effectiveness of the international traffic blockade.

Methods

In this situation, this study takes Shanghai as an example to propose a new type of infectious disease prediction model. The model first uses the sparse graph model to analyze the international epidemic spread network to find countries and regions related to Shanghai. Next, multiple regression models were used to fit the existing COVID-19 growth data in Shanghai. Finally, the model predicts the growth curve of the COVID-19 epidemic in Shanghai without an international traffic blockade.

Results

In this study, by constructing a sparse graph network model, 30 countries and regions related to Shanghai's overseas epidemic input were obtained, such as the United States. Moreover, the three regression models in this paper have obtained a good fitting effect. Finally, using data from 30 countries and regions related to Shanghai from April 4 to April 19 for a 15-day short-term forecast and comparing with real data, the results show that Shanghai's international traffic blockade is effective and necessary.

Conclusion

This research shows that the control measures taken by Shanghai are very effective. At present, more and more countries and regions will face the current situation in Shanghai. We recommend that other countries and regions learn from Shanghai's successful experience in preventing overseas imports in order to fully prepare for epidemic prevention and control.

Keywords: COVID-19, overseas imports, Shang Hai, Gaussian sparse network model, regression model

Background

Since December 2019, COVID-19 broke out in Wuhan, Hubei Province, China. Coronavirus disease (COVID-19) caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This virus quickly spread throughout China. In the early stages of the COVID-19 epidemic, the number of infected cases increased exponentially[1]. The Chinese government has taken various preventive and control measures to intervene, including mandatory blockades, staggered working hours, etc.[2-4]. These measures effectively prevent the virus from spreading from person to person, and reduce the morbidity and mortality[5]. After more than two months, COVID-19 was gradually controlled in China and entered a stable state.

In view of the fact that the COVID-19 epidemic in China has been basically contained, other international regions of the world are still experiencing outbreaks. Unless substantive public health interventions are implemented, overseas countries and regions that have close communications with China may cause the epidemic in China to escalate again. Among them, Shanghai, as one of China's largest international airports, is the region with the highest risk of overseas imports. Overseas case importation poses a huge threat to this city with a population of 24 million. As of 24:00 on April 2, 2020, there were 1562 confirmed cases in China, including 698 confirmed cases imported from abroad. The number of confirmed cases in Shanghai is 177, including 171

imported cases abroad. Therefore, in order to solve this problem. The Shanghai government has taken a lot of measures, including isolation observation, traffic control, and nucleic acid detection, etc. It is worth noting that from March 28th, Shanghai suspended the entry permit for non-Chinese nationals.

We also note that apart from Shanghai, many other regions in the world also face the same problem as Shanghai, that is, what measures should be used to control the import of overseas cases? Since the outbreak of Wuhan, several modeling research teams around the world have used an infection model based on the SIR or SEIR framework to estimate and predict COVID-19[6-8]. However, the existing models are difficult to be directly applied to the prediction of overseas case trends. In this article, we propose a sparse relationship graph model for the establishment of an international epidemic spread network. After combining the regression model, we can predict the growth trend of cases in the target area. Because Shanghai, China is one of the earliest areas to take measures to block overseas spread. Therefore, this article takes Shanghai as an example, on the one hand, we want to verify the model proposed in this paper. On the other hand, we want to analyze whether the epidemic prevention and control measures taken by Shanghai are effective and whether Shanghai's measures can provide an effective reference for similar regions.

We used 77-day real diagnosis data of 188 countries and regions around the world, and established an international network related to Shanghai. We discover that the epidemic trend

* Correspondence: yongliangresearch@gmail.com

¹ Faculty of Information Technology, Macau University of Science and Technology, Macau, 999078, China.

² State Key Laboratory of Quality Research in Chinese Medicines, Macau University of Science and Technology, Macau, 999078, China.

³ Guangdong-Hong Kong-Macao Joint Laboratory for Smart Discrete Manufacturing, Guangzhou 510006, China.

in Shanghai is highly correlated with the epidemic situation in 30 countries and regions and most of these countries and regions are the center of the outbreak of the international epidemic. We established a variety of regression models to fit the existing growth curve, and predicted the growth of Shanghai cases from April 4th to 19th without blocking international traffic. This study believes that Shanghai's blockade measures are necessary and effective, which avoids greater losses and effectively reduces the risk of secondary epidemics for China. We suggest that other countries learn from Shanghai's successful experience and prepare well in advance when the next battle arrives.

89 Methods

nodes with large existence are called central points. For this study, our main focus is on nodes related to Shanghai. In the relationship network, if the model thinks that a country or region is related to Shanghai, it means that the epidemic situation in that country can affect the growth of cases in Shanghai. The mathematical framework of the sparse network model based on regularization in this paper is as follows[9]:

Consider the n -dimensional multivariate normal distributed random variable Equation (1):

$$C = (C_1, \dots, C_n) \sim N(\mu, \Sigma) \quad (1)$$

This includes Gaussian linear models. For example, C_1 is the response variable, $\{C_k; 2 \leq k \leq n\}$ is a predictor. Assuming that the covariance matrix is nonsingular, you can use the graphical model $G = (\Gamma, E)$ conveniently express the conditional independence structure of the distribution. In $\Gamma = \{1, \dots, n\}$ is the set of nodes, and E is the set of edges in C . Given all remaining variables $C \setminus \{a, b\} = \{C_k; k \in \Gamma \setminus \{a, b\}\}$, A pair of (a, b) is included in the edge set E if and only if C_a depends conditionally on C_b . Given all remaining variables, each pair of variables not included in the edge set is conditionally independent and corresponds to the zero term in the inverse covariance matrix[10].

Neighborhood selection is a sub-problem of covariance selection. The minimum subset of the neighborhood $\Gamma \setminus \{a\}$ of the node $a \in \Gamma$, therefore, considering all the variables C_a in the neighborhood, C_a is conditionally independent of all remaining variables. The neighborhood of node $a \in \Gamma$ consists of all nodes $b \in \Gamma \setminus \{a\}$, so $((a, b) \in E)$. For the observation of C , neighborhood selection aims to estimate (individually) the neighborhood of any given variable (or node). Neighborhood selection can be used as a standard regression problem, it can be effectively solved with L_1 [11]. As will be shown in this paper.

For sparse high-dimensional graphs, the consistency of the proposed neighborhood selection will be shown, where the number of variables may grow with any power of the number of observations (high-dimensional), whereas the number of neighbors of any variable is growing at most slightly slower than the number of observations (sparsity).

Neighborhood selection with the L_1 . It is well known that the Lasso, introduced by Tibshirani [8], and known as Basis Pursuit in the context of wavelet regression[12]. With simplicity [10]. When the forecast has all remaining variables $C_a \setminus \{C_k; k \in \Gamma \setminus (n) \setminus \{a\}\}$, The estimated value of the disappeared lasso coefficient asymptotically identifies the neighborhood of node a in the graph, as shown below. Let $n \times c_{(n)}$ -dimensional matrix C contain c independent n observations, so for all $a \in \Gamma(n)$, column C_a corresponds to a vector of n independent observations.

90 data source

The data in this article comes from the Johns Hopkins University Repository, mainly from January 19 to April 19, 2020, the number of daily diagnoses in various countries and regions around the world.

95 Model of international relations network based on L_1

In order to discover the international correlation network of COVID-19, we build a sparse network model based on regularization. As the name implies, the network obtained by this model is a directionless network. The typical characteristic of a directionless network is that the degree between most nodes in the network is very small, the few

Let $\langle \cdot, \cdot \rangle$ on $\mathbb{R}_n$ be the usual inner product, and $\|\cdot\|_2$ the corresponding norm.

The L_1 estimate $\theta^{a,\lambda}$ of θ^a is given by Equation (2):

$$\hat{\theta}^{a,\lambda} = \arg \min_{\theta: \theta_a=0} (n^{-1} \|C_a - C_\theta\|_2^2 + \lambda \|\theta\|_1) \quad (2)$$

$\|\theta\|_1 = \sum b \in \Gamma(n) |\theta_b|$ is the L_1 -norm of the coefficient vector. It is recommended to normalize all variables to a common empirical variance in the above formula. The solution of the above formula is not necessarily unique. However, if the uniqueness fails, the solution set is still convex, and all of our results on the neighborhood apply to any solution of the above formula.

Other regression estimates based on the lp norm have been proposed, where p is usually in the range $[0, 2]$ (see[13]). A value of $p = 2$ will result in ridge estimation, while $p = 0$ corresponds to traditional model selection. As we all know, only when $p \leq 1$, the estimated value has a parsimony property (some components happen to be zero). For $p \geq 1$, the optimization problem in the above formula is only convex. Therefore, the minimization of empirical risk constrained by L_1 occupies a unique position, because $p = 1$ is the only value of p , variable selection is made at this value, and the optimization problem is still convex, so it is feasible for high-dimensional problems.

The neighborhood estimate (parameterized by λ) is defined by the non-zero coefficient estimate of L_1 penalty regression Equation (3):

$$\hat{n}e_a^\lambda = \{b \in \Gamma(n): \hat{\theta}_b^{a,\lambda} \neq 0\} \quad (3)$$

Therefore, each choice of penalty parameter λ specifies an estimate of the neighborhood of node $a \in \Gamma(n)$, and the rest is to choose the appropriate penalty parameter. A larger penalty value tends to reduce the size of the estimated set, and if the value of λ decreases, usually more variables are included in the estimated value.

The prediction-oracle solution. A seemingly useful choice of penalty parameters is (unavailable) to predict the oracle value Equation (4):

$$\lambda_{oracle} = \arg \min_{\lambda} E(C_a - \sum_{k \in \Gamma(n)} \hat{\theta}_k^{a,\lambda} C_k)^2 \quad (4)$$

Expectation is understood to be abo has nothing to do with samples that estimate $\theta^{a,\lambda}$. The prediction penalty minimizes the prediction risk in all L_1 regular sub-estimates. The λ_{oracle} estimate is obtained by selecting λ_{cv} for cross-validation.

Shao[14] showed that for L_0 penalty regression, the cross-validation choice of penalty parameters is consistent with the model choice of the verification set size under certain conditions. Predicting that the Oracle solution will not lead to consistent model selection for L_1 , as shown in the simple example below.

192 Proposition. Let the number of variables grow to infinity, for
 193 $n \rightarrow \infty, p(n) \rightarrow \infty$, for some $\gamma > 0$ with $p(n) = o(n^\gamma)$,
 194 Assume that the covariance matrices $\Sigma(n)$ except for some pair
 195 $(a, b) \in \Gamma(n) \times \Gamma(n)$, for which $\Sigma_{ab}(n) = \Sigma_{ba}(n) = s$, for
 196 some $0 < s < 1$ and all $n \in \mathbb{N}$. under the prediction-oracle
 197 penalty, The probability of choosing the wrong neighborhood for
 198 node a converges to 1, as shown in Equation(5):

$$199 \quad P(\widehat{ne}_a^{\lambda_{oracle}} \neq ne_a) \rightarrow 1 \quad \text{for } n \rightarrow \infty \quad (5)$$

200 From the proof of the above proposition, it can be concluded
 201 that many noise variables are included in the prediction of the
 202 neighborhood of the Oracle solution. In fact, for a fixed number
 203 of variables, the possibility of including noise variables in
 204 prediction predictions will not even disappear. If the selected
 205 penalty is greater than the predicted optimal value, then the L_1
 206 regularizer can be used for consistent neighborhood selection.

207 Regression model

208 After establishing a global epidemic spread relationship network
 209 and identifying relevant countries and regions in Shanghai. In this
 210 paper, three regression models are established for experiments
 211 including: nuclear ridge regression model, elastic network model
 212 and Bayesian regression model.

213 Kernel Ridge Regression

214 For the parameter matrix, in order to solve the risk of overfitting,
 215 we sequentially add "kernel" and "ridge" to the linear regression
 216 model to transform the model[15].

217 The first step is to add "kernel". For a given test sample, each
 218 training sample $\vec{x}_i$ contains a coefficient α_j , so the loss function
 219 can be expanded as shown in Equation (6).

$$220 \quad \sum_{i=1}^n (y_i - \sum_{j=1}^n \alpha_j k(\vec{x}_j, \vec{x}_i))^2 \quad (6)$$

221 This is a quadratic loss function. We choose the appropriate α_j
 222 to maximize it.

223 The second step, adding "ridge", is actually adding
 224 regularization terms, adding an L_2 regularization on the basis of
 225 linear regression. Then the loss function becomes shown in
 226 Equation (7).

$$227 \quad \sum_{i=1}^n \left(y_i - \sum_{j=1}^n \alpha_j k(\vec{x}_j, \vec{x}_i) \right)^2 + \lambda \|\psi\|_{\mathcal{H}}^2 \quad (7)$$

228 The second summation part of the above formula will penalize
 229 large coefficients, which can prevent the model from giving a
 230 large weight to a single training example and overemphasizing
 231 the role of a single training example, the parameter λ controls the
 232 trade-off between the degree of fitting and the complexity of the
 233 model. $\mathcal{H}$ is Hilbert space, $\|\cdot\|_{\mathcal{H}}$ is a 2-paradigm under Hilbert
 234 space. Expanding the regularization term, the loss function can be
 235 changed to the form shown in Equation (8).

$$236 \quad \sum_{i=1}^n (y_i - \sum_{j=1}^n \alpha_j k(\vec{x}_j, \vec{x}_i))^2 + \lambda \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j k(\vec{x}_j, \vec{x}_i) \quad (8)$$

237 Among them, K is a matrix of $n * n, kn, m = k(\vec{x}_n, \vec{x}_m)$. $\vec{y}$ is
 238 a vector of n labels.

239 Elastic network

240 Elastic network is a linear regression model trained using L_1 and
 241 L_2 norms as a priori regular terms[16]. This model can fit non-
 242 zero sparse matrices with a small number of parameters. Elastic
 243 networks are very useful when many features are interrelated.

244 Elastic networks are more inclined to consider two of these
 245 characteristics randomly, and inherit the stability of Ridge during
 246 the allowed cycle[17].

247 Here, the objective function of minimization is shown in
 248 Equation (9).

$$249 \quad \min_w \frac{1}{2n_{samples}} \|Xw - y\|_2^2 + \alpha \rho \|w\|_1 + \frac{\alpha(1-\rho)}{2} \|w\|_2^2 \quad (9)$$

250 Bayesian Ridge Regression

251 Bayesian Ridge Regression is to use the probability model to
 252 estimate the regression model, mainly to solve the complexity of
 253 the model in the process of maximum likelihood estimation[18].
 254 The process of Bayesian Ridge regression is a process in which
 255 sample points are gradually added to the learner. The posterior of
 256 the previous sample point will be used as a priori by the next
 257 estimation. In other words, Bayesian learning is gradually
 258 updating the prior. The prior update is actually iterated by
 259 updating the maximum likelihood estimation parameter and
 260 sample points, the prior parameter ω is obtained by the Gaussian
 261 mode Equation (10).

$$262 \quad p(w|\lambda) = \mathcal{N}(w|0, \lambda^{-1}I_p) \quad (10)$$

263 The prior parameters α and λ generally follow the gamma
 264 distribution, and this distribution has a conjugate prior
 265 relationship with Gaussian [19]. The parameters ω , α and λ are
 266 estimated together when the model is fitted, where the parameters
 267 α and λ are obtained by maximum likelihood estimation.

268 The difference between Bayesian Ridge Regression and
 269 ordinary Ridge Regression is that it adopts Bayesian strategy of
 270 updating priors' step by step. Ordinary Ridge Regression allows
 271 the parameter to be zero, but Bayesian Estimation cannot do so
 272 because the standard deviation of Gaussian Can be infinite. At the
 273 same time, Bayesian regression will give the confidence interval
 274 of the parameter, which is an optional range of the parameter,
 275 which is essentially a covariance matrix.

276 Results and discussion

277 This chapter first uses the case data of 188 countries and regions
 278 in the world from January 19 to April 4 to accumulate a total of
 279 77 days to establish a global epidemic transmission relationship
 280 network. Next, the subnet data of countries related to Shanghai
 281 are extracted. Then, three regression models were used to
 282 establish regression models to fit the cumulative case growth data
 283 from January 19 to April 4 in Shanghai. This article mainly uses
 284 the 5-fold cross-validation, explained_variance, mean_absolute_error,
 285 mean_squared_error and r2 indicators to verify the model results. Finally, through the regression model
 286 after training, we predicted the cumulative diagnosed cases in
 287 Shanghai from April 4 to April 19(without blocking traffic).
 288

289 Global network analysis

290 According to the latest China national epidemic prevention and
 291 control instructions "anti-import, non-proliferation", the
 292 Shanghai government responded to the Chinese government's call.
 293 On March 28, 2020, the entry application for non-Chinese
 294 nationals was stopped. The infection period of COVID-19 seems
 295 to be very long, which may last 10 days or longer after the
 296 incubation period [20]. Considering the special situation, we
 297 chose a latency of 7 days. Therefore, through the sparse network
 298 model based on L_1 , we constructed the data matrix of the actual
 299 case statistics of 188 countries and regions in the world from
 300 January 19th to April 4th, and plotted the COVID-19 international

301 network. As shown in Figure 1, by analyzing the international
 302 relations network, we have counted the central nodes of the
 303 international epidemic transmission network, As shown in Table
 304 1, we found that the United States, Italy, Iran, and Hubei, China
 305 are the main Hub nodes, that is, the main international epidemic
 306 spread countries. This result is consistent with the existing real
 307 situation; Therefore, it can be concluded that the international
 308 network relations based on L_1 in this study have certain reliability.

309 Shanghai Subnet Analysis

310 Next, we extracted the relationship subnets of cities and regions
 311 related to Shanghai. as shown in Figure 2. We can see that
 312 Shanghai is closely related to many areas of China, such as Hubei,
 313 Guangdong, Beijing and Heilongjiang. This is because in the

314 early days of the spread of the Shanghai epidemic, these areas
 315 were the main import areas to Shanghai. At present, the epidemic
 316 situation in these areas has been stable and basically contained.
 317 As shown in Figure 2, we can also find many international
 318 communication channels, such as: The United States, European
 319 countries, Iran, the Philippines and other regions, this is caused
 320 by COVID-19 broke out in the international scope, brought by
 321 passengers entering international flights Input abroad. After
 322 identifying 30 countries and regions related to Shanghai, we can
 323 further establish a regression model to fit the epidemic growth
 324 data of Shanghai from January 19 to April 4.
 325

Figure. 1. COVID-19 International Relations Network in 188 countries and regions

Figure .2. COVID-19 International Relations Network in 30 countries and regions related to Shang Hai

Figure .3. Comparison of cumulative confirmed cases and actual values predicted by the three regression methods

Figure 4. Comparison between predicted and actual values (unblocked international traffic)

TABLE I
HUB NODES IN THE INTERNATIONAL EPIDEMIC RELATIONSHIP NETWORK

Country	United States	France	Germany	Italy	Iran	Hubei, China
Number of nodes	183	183	183	181	180	180

TABLE II
THE RESULTS OF THREE REGRESSION METHODS BASED ON 5-FOLD VERIFICATION

	0	1	3	4	5
KernelRidge	-7.8	0.62	-11.51	-12.12	-18.64
BayesianRidge	-12.14	-2.6	-21.18	-7.6	24.04
ElasticNet	-10.68	0.92	-5.41	-0.17	-22.78

TABLE III
PERFORMANCE OF DIFFERENT INDICATORS OF THE THREE REGRESSION MODELS

	ev	mae	mse	r2
KernelRidge	0.996	3.39	43.12	0.996
BayesianRidge	0.997	2.82	31.10	0.997
ElasticNet	0.997	3.19	29.68	0.997

TABLE IV
COMPARISON BETWEEN PREDICTED AND ACTUAL VALUES (UNBLOCKED INTERNATIONAL TRAFFIC)

	KernelRidge	BayesianRidge	ElasticNet	Real
April 5	379	370	378	371
April 6	422	415	414	380
April 7	450	440	446	394
April 8	471	468	487	404
April 9	529	541	552	414
April 10	545	553	590	433
April 11	684	671	684	451

April 12	755	705	741	468
April 13	846	807	884	485
April 14	960	871	999	492
April 15	1014	915	1076	498
April 16	1106	946	1144	509
April 17	1136	1022	1239	516
April 18	1211	1091	1347	522
April 19	1275	1154	1386	526

326 Building a regression model

327 This article uses three regression algorithms to build the model,
 328 which are: KernelRidge, BayesianRidge and ElasticNet model.
 329 As shown in Figure 3 and Table 2-3, the three methods can fit the
 330 existing growth data in Shanghai well. Among them, the
 331 ElasticNet model performs best, explained_variance ,
 332 mean_absolute_error, mean_squared_error and r2 values Only
 333 0.997, 3.19, 29.68 and 0.997, respectively, the average loss value
 334 of the 5-fold cross-validation is only -6.624. It can also be seen
 335 from the fitting curve that this method shows a good fitting
 336 effect. Experiments have proved that without blocking
 337 international traffic in Shanghai, the real data of the countries and
 338 regions related to Shanghai in the above international relations
 339 network can effectively predict the growth of cases in Shanghai.

340 Short-term epidemic growth curve (unblocked 341 international traffic)

342 After establishing a regression model, we use data from 30
 343 countries and regions related to Shanghai from April 4 to April
 344 19 for 15 days to predict Shanghai's epidemic growth curve
 345 without the international traffic blockade, and compare it with
 346 real data. The experimental results are shown in Figure 4 and
 347 Table 4. On the premise that international traffic is not blocked,
 348 all three regression models have concluded that the cumulative
 349 number of confirmed cases will far exceed the existing real data.
 350 On April 19th, the cumulative case prediction results of the three
 351 models were between 1154-1386 people. In fact, the cumulative
 352 confirmed cases on that day were 526, and the predicted data was
 353 slightly greater than twice the true confirmed cases. The result of
 354 this comparison shows that Shanghai's adoption of the
 355 international traffic blockade has a significant effect and can
 356 largely prevent the import of overseas epidemic situations. It also
 357 means that Shanghai's traffic control is effective and necessary.

358 Conclusion

359 COVID-19 quickly spread from a city to the entire country in just
 360 30 days. This alarming rate of expansion and the number of cases
 361 growing shocked the public health service system of the entire
 362 country. The Chinese government showed to the world its
 363 epidemic response capacity in the first time. These measures have
 364 made a significant effect in responding to COVID-19. China's
 365 domestic epidemic situation has been basically blocked. At
 366 present, COVID-19 has broken out in many countries outside the
 367 country. Therefore, at this stage, the main way of confirmed cases
 368 in China is passengers entering by international transportation.

369 This article establishes a network of epidemic transmission
 370 relationships between Shanghai and different countries and
 371 regions around the world, and builds a regression model based on
 372 network information to fit Shanghai's COVID-19 epidemic

373 growth data. The results show that the regression model based on
 374 the relational network can better fit the existing cumulative
 375 number growth curve. Combined with the regression model, we
 376 can predict the future development trend of cumulative cases in
 377 Shanghai (unblocked international traffic). According to the
 378 prediction results, we learned that the Shanghai government
 379 adopted traffic blockade measures, which effectively prevented
 380 the epidemic from spreading further. At present, the imported
 381 epidemic situation outside Shanghai has been effectively
 382 controlled, but we still need to be vigilant to prevent the
 383 recurrence of the epidemic situation. More importantly, with the
 384 effective control of the local epidemic situation in various
 385 countries, Shanghai's successful experience in dealing with the
 386 import of overseas epidemic situations has also played a
 387 demonstration role for other countries and regions.

388 In order to reduce the risk of imported COVID-19 cases,
 389 Shanghai has adopted a series of measures to prevent and control
 390 possible overseas imported cases, strengthen monitoring and
 391 rapid identification of possible cases. First, during the epidemic,
 392 all Chinese and foreign personnel who have lived in key countries
 393 or regions within 14 days before entering Shanghai will be
 394 quarantined for 14 days. Secondly, conduct temperature
 395 examination and medical observation on all entry personnel, and
 396 then transfer and isolate confirmed cases and suspected cases for
 397 rapid treatment. Carry out preventive measures for close contacts.
 398 Since March 28, international routes have been suspended, and
 399 foreign tourists are prohibited from entering Shanghai.

400 As a successful import case for overseas epidemic prevention,
 401 Shanghai has fully demonstrated how a region can prevent a
 402 global pandemic, and it has provided a good demonstration for
 403 other countries and regions. At the same time, it also showed the
 404 friendly style of the Chinese nation and treated all immigrants
 405 equally during the epidemic, making foreign friends feel warm
 406 during this difficult time.

407 Abbreviations

408 COVID-19: Coronavirus disease 2019;

409 Ethics Approval and Consent to participate

410 Not applicable.

411 Consent for publication

412 Not applicable.

413 Availability of data and materials

414 All data supporting the findings of this study are included in the
 415 article.

416 Competing interests

417 The authors declare that they have no competing interests.

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Authors' contributions

Q. Dang, R. Miao and Y. Liang conceived the paper. Q. Dang, R. Miao performed the literature search, prepared the figures, and interpreted the data. Q. Dang, wrote the first version of the manuscript. R. Miao and Y. Liang assisted in the restructuring and revision of the manuscript. All authors read, contributed to, and approved the final version.

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Authors' information

1. Faculty of Information Technology, Macau University of Science and Technology, Macau, 999078, China. 2. State Key Laboratory of Quality Research in Chinese Medicines, Macau University of Science and Technology, Macau, 999078, China. 3. Guangdong-Hong Kong-Macao Joint Laboratory for Smart Discrete Manufacturing, Guangzhou 510006, China.

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Figures and legends

Figure. 1. COVID-19 International Relations Network in 188 countries and regions

Figure. 2. COVID-19 International Relations Network in 30 countries and regions related to Shang Hai

Figure .3. Comparison of cumulative confirmed cases and actual values predicted by the three regression methods

Figure 4. Comparison between predicted and actual values (unblocked international traffic)

Figures

Figure 1

COVID-19 International Relations Network in 188 countries and regions

Figure 2

COVID-19 International Relations Network in 30 countries and regions related to Shang Hai

Figure 3

Comparison of cumulative confirmed cases and actual values predicted by the three regression methods

Figure 4

Comparison between predicted and actual values (unblocked international traffic)