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Spatiotemporal representation learning for rescue route selection: An optimized regularization based method

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ABSTRACT

Emergency medical services (EMS) are emergency services that provide urgent pre-hospital treatment for serious illness and injuries. However, in most countries, EMS is faced with the problem of untimely emergency response. In this paper, we develop an Optimized Regularization based framework (OpRe-RRS) by optimizing the Rescue Route Selection problem to increase the rescue speed. Specifically, through the analysis of spatio-temporal data, we predict the ranking of road priority and select the rescue route for ambulances to lift speed. Along this line, we match the GPS data of ambulances to the correct road section through a map matching algorithm. Then, we extract different features from three perspectives: (i) basic features, (ii) POI features and (iii) traffic features. To effectively exploit the roads similarity, we develop a loss function with regularization to solve this prediction problem. Finally, experiments on real-world data demonstrate that our method can effectively reduce rescue time.

1. Introduction

Emergency medical services (EMS), also known as ambulance services or paramedic services, are emergency services that provide urgent pre-hospital treatment and stabilisation for serious illness and injuries and transport to definitive care.[1] One second in advance for emergency response may save more lives. As an important medical resource, ambulances guard the lifeline of patients. However, in most countries, due to the scarcity of medical resources, whether in remote areas with relatively scarce resources, or in urban hubs where in short supply, they are faced with various degrees of untimely emergency response and limited ambulance response range.

A poll found that,[2] in 2019, as the number of drug addicts, homeless people and mental patients increases, 911 calls are surging throughout San Francisco, putting a massive strain on paramedics. The service of the ambulance reaches the “level zero” status every day. One of these situations occurred on August 25, the city’s ambulance coverage dropped below “level zero”[3] 25 times meaning at least one call for help was waiting. This situation has seriously threatened the lives of the local people.

The internationally required response time for pre-hospital first aid is 5–10 min. The level of pre-hospital medical emergency services is uneven due to the uneven economic development in different regions (Wang et al., 2006). Although each country has set high emergency response targets and standards, in actual rescue, untimely response is still more than a problem faced by countries. How to improve the response speed of pre-hospital first aid and reduce the response time of ambulances is still an important issue. The current research on improving emergency response speed and shortening emergency rescue time mainly revolves around the dispatching of ambulances (Jagtenberg et al., 2015; Schmid, 2012) and the relocation of emergency centers (Chen et al., July 2016; Erkut et al., 2008). However, few researches on path selection of ambulances (Talarico et al., 2015) also have important theoretical significance and practical value for pre-hospital emergency planning and management.

Concentrated on the driving environment of ambulances, we propose a method (OpRe-RRS) based on spatio-temporal data to effectively shorten the rescue time of ambulances. We select the suitable driving

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[1] https://en.wikipedia.iwiki.eu.org/wiki/Emergency_medical_services.
[2] https://www.ktvu.com/news/911-calls-in-san-francisco-surge-leaving-ambulance-service-at-level-zero-on-a-daily-basis.
[3] One of the “level zero” activation criteria: extreme demand for EMS resources resulting in either an ambulance shortages and/or saturation of all hospitals (ambulance shortage must exceed 30 min).

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routes for the ambulances based on the method, directly improving the level of emergency medical care.

Specifically, we obtain information from three types of data: (1) road network data, (2) POI (point of interest) data, and (3) ambulance trajectory data. Road data and POI data are combined to detect and extract the basic features and POI features of roads. Then we perform trajectory matching to match the trajectory points of the ambulances to the correct roads. Based on the matched results, we obtain the paths traveled by ambulances and then calculate the traffic features of roads: the average speed and variance of ambulances driving on the road. In the next, we establish a predictive model. Based on the similarity of roads and the dependence of the road's priority score, we propose two norms to be added to the model as regularization terms. Our model predicts the priority of roads, which can be applied to the task of selecting paths for ambulances. Finally, we evaluate the proposed method over a real-world dataset involving 68 ambulances, and the experimental results show that our method consistently provides better performance compared with other method such as BP, SVR, RFR and RankNet. In the application part, we add road priority as a factor to the ambulance rescue route selection.

The rest of this paper is organized as follows. A literature review is presented in Section 2. Section 3 introduces the problem statement and framework overview. The data preprocessing work is completed in Section 4. Section 5 and 6 develop the OpRe-RRS model and presents the experimental results. Finally, Section 7 discusses of the implications and future research directions.

2. Literature review

The current works on improving emergency response speed and shortening emergency rescue time are mainly divided into two groups, "facility" group and "service" group.

The "facility" method means adding or changing some hardware facilities, which is mainly to increase emergency resources, such as purchasing more ambulances, relocating emergency stations, etc.

Previous works measure spatial proximity under Euclidean space or static road network to tackle the problem of selecting the appropriate locations for ambulance stations. The large-scale vehicle mobility data help understanding urban structures and crowd dynamics (Jiang et al., 2020). Current works propose to locate the ambulance stations by using the data-driven approach for that the area can be covered is maximized. Li et al. (2015) estimate the travel-time of road segments using real GPS trajectories and set the objective function as the MinSum model. They propose an efficient PAM-based refinement for the location problem to solve the NP-hard problem, which can reduce the travel-time to reach the emergency requests by 29.9% when compared to the original locations of ambulance stations. However, in practical application, building facilities is a large-scale reconstruction project and the cost is too high. The results of the research works are not well accepted by the governments to locate the ambulance stations.

The "service" method is mainly to improve the response speed by improving the utilization and efficiency of existing resources without changing the existing facilities. Many previous methods have been proposed, such as redistributing ambulances and rescheduling ambulances, identifying potential hazards and rescue demands (Balcik et al., 2019; Zhou and Matteson, 2015).

Redistributing ambulances is an early covering location problem. The number of ambulances is fixed and one aims to find the optimal locations of these ambulances, such that the response time is minimized. It assumes that, after completing a mission, each ambulance will return to its designated standby site (Blanger et al., 2019). Cherkesly et al. (2019) solve the location-path coverage problem (LRCP), develop tools to assist in the design and analysis of community healthcare networks, and improve the coverage of medical insurance in underserved areas.

Within a 24-h cycle, the demand, travel time, ambulance speed and coverage area change. Taking these changes into account, Degel et al. (2015) and van Buuren et al. (2018) propose a new dynamic method based on data-driven optimization to ensure rescheduling ambulances closer to realistic demand.

Dynamic rescheduling ambulances typically operate in real time. Therefore, a reschedule strategy needs to be obtained in a very short time. As a consequence, most literature on dynamic relocation models concentrate on heuristics (Benabdouallah et al., 2016). Alanis et al. (2013) propose and analyze a two-dimensional Markov chain model that repositions ambulances, which is combined with heuristic search methods. This model optimizes the compliance table policies: a relocation strategy commonly used in practice, which prescribe desired locations for the idle ambulances, and are computed in the work of Gendreau et al. (2006) using an integer program. To compute efficient compliance tables, van Barneveld (2016) introduce the minimum expected penalty relocation problem (MEXPREP) and outperform both the static policy and compliance tables.

Some new reinforcement learning methods are also utilized in the problem of dynamic ambulances relocation. Based on the learned deep scoring network, Ji et al. (2019) propose an effective dynamic ambulance redeployment algorithm. Liu et al. (2020) propose RedCon-DQN by considering multiple scheduling interactive factors, which is based on Deep Q-value Network (DQN) and can output the optimized redeployment policy given specific environment.

Previous works are based on the location of facilities and ambulances, for the purpose that the number and response speed of ambulances can be guaranteed in time when the rescue demands occur. However, few works concentrate on the driving environment of ambulances during rescue. Considering the patterns and surrounding conditions of the road, we study the suitable driving routes of the ambulances, and add findings to the route selection of the ambulances, so as to improve the speed of the ambulances driving in the rescue process. It is also an effective choice to directly shorten the driving time of the ambulances by optimizing the driving routes of the ambulances.

3. Problem statement and framework overview

In this section, we first introduce the preliminaries, then present the problem formulation followed by framework overview.

3.1. Preliminaries

Definition 1. Spatio-temporal Data. Spatio-temporal data are the data that has both time and space dimensions. Spatio-temporal data usually include time information, space information, and attribute information.

Definition 2. Trajectory. A trajectory is a sequence of spatial points arranged in chronological order, $T_r : p_1 \rightarrow p_2 \rightarrow \ldots \rightarrow p_n$. Each point $p = (l, t, v)$ has a geographic space coordinate l and a time stamp t. In particular, the point can also record the velocity v at which the trajectory point is generated.

Definition 3. Point of Interest (POI). POI is a non-geographically meaningful point in the physical world. In a geographic information system, a POI can be a hospital, a shop, a school, a bus stop, etc. Geographically significant coordinates do not belong to POI, such as cities, rivers, mountains, etc. Each POI has name, address, coordinates, category and other information.

Definition 4. Road Network. A road network refers to a road system composed of a group of interconnected road sections in a certain area and interwoven into a network. In a road network graph $G = (V, E)$, the vertex set V represents the intersection, and the edge set $E = e$ represents all relevant road sections. Road segment r is a directed edge with two end points, and contains its own characteristic information, such as the length of the road segment $r.len$, the road level $r.lev$ (for example, highways or ordinary streets), the road segment direction $r.dir$, and so on.

3.2. Problem formulation

Given a road network graph $G = (V, E)$, the data-driven ambulance lane planning problem aims to predict the order of road sections related to the recommendation degree, It follows two standards: (i) the faster average speed of the ambulance on the road section is, the higher recommendation degree, (ii) the lower variance of the ambulance vehicles' speed on the road section, the higher recommendation degree. In order to achieve this goal, a prediction model through the existing road data can be obtained to predict the recommendation degree of the road section. Based on the recommendation degree ranking of all roads, we solve the problem of emergency route selection for ambulances.

Problem definition: Given a set of road segments $G' = (V', E')$, each road segment has basic road features f_r: road length $r.len$, road level $r.lev$, connection number $r.con$, tortuosity $r.tor$, POI quantitative feature f_p, road traffic feature M_r: average speed $r.v$ and variance $r.d_v$. We aim to find a functional model to predict the recommendation degree through feature combination, and ranks the recommendation degree of all roads $G = (V, E)$ to maximize the accuracy of the ranking.

3.3. Framework overview

The overview of our proposed prediction framework (OpRe-RRS) is illustrated in Fig. 1:

Along this line, we extract physical road features and POI features of road network data. Then, we match the GPS data of ambulances based on time to the correct road section through the map matching algorithm. After inverted index construction, we obtain the traffic features. Using the different features from three perspectives, we set the independent variable and the dependent variable. We develop a linear loss function with regularization to solve this prediction problem. Finally, experiments on real-world data demonstrate that our method can effectively improve the emergency response speed of ambulances.

4. Data preprocessing

The section of data preprocessing introduces the trajectory matching that matches GPS trajectory data to road network data. Based on the paths traveled by ambulances, the physical road features and the traffic features are extracted.

4.1. Trajectory matching

The most intuitive method of map matching is to match GPS points with the nearest road node or road segment, but this method generally causes relatively large errors. Therefore, we endeavor to add other geometric methods (Greenfeld, 2002) on the basis of matching the nearest road section to improve the matching accuracy. Therefore, the map matching process consists of two steps: the first step is to match all points to the nearest road section, then add the similarity in orientation, the proximity of the point to the line and the intersection to improve the matching accuracy based on the initial matching.

4.2. Feature extraction

Two types of features are extracted from the matched spatio-temporal data and road network data (Shang et al., 2014). One is a set of physical features extracted from POI and road network data to describe the geographical environment of the road section. The second is the driving mode characteristics of the ambulance extracted from the spatio-temporal data.

4.2.1. Physical road features

Fig. 2 shows the topology of a road network with 9 vertexes and 12 edges.

Basic features of road f_r: road length $r.len$, road level $r.lev$, connection number $r.con$, tortuosity $r.tor$.The tortuosity $r.tor$ of the road section is the ratio of the length of the road section $r.len$ to the Euclidean distance between the two ends of the road section, as shown in Fig. 2, $r.tor = r.len/d$.

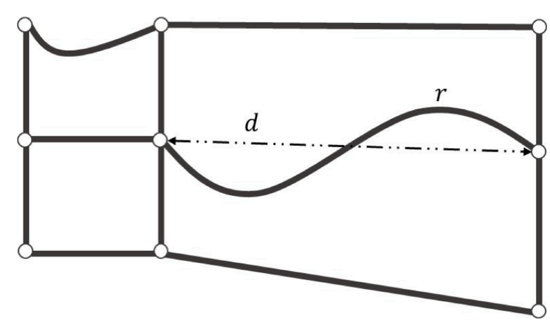

Fig. 2. The Basic Road Structure.

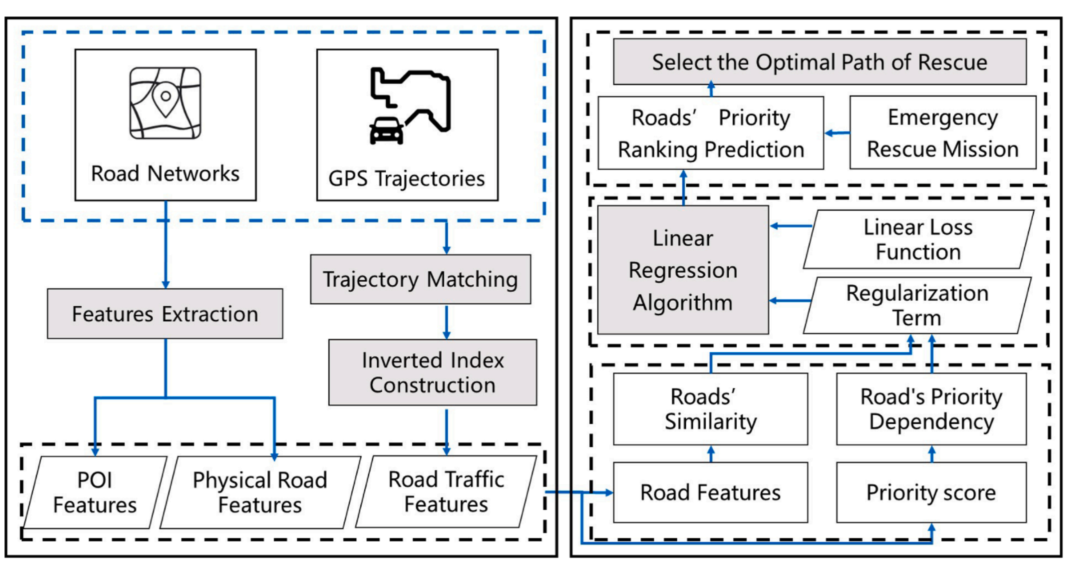

Fig. 1. The Framework Overview of OpRe-RRS.

In Fig. 2, the number of road connections $r.con_1$ and $r.con_2$ are 3 and 2, respectively. The total number of road connections in section r is 5, $r.con = r.con_1 + r.con_2$.

POI feature $r.f_p$: Calculate the distribution of POI around the two ends of the road (within a circle of 100 meters) in the following 12 types of POI: medical and health, hotels, restaurants, leisure and entertainment, news media, education and scientific research, financial services, social services, shopping malls, transportation hubs, transportation service facilities, public places.

For example, the POI distribution of the road segment numbered 75 (Huangshan Road) is $(0,0,2,3,0,0,2,0,1,0,2,0)$.

4.2.2. Road traffic features

After the map is matched, each point of the trajectory is mapped to the road section, and the mean and variance of the speed of all ambulance vehicles passing through a fixed road section are calculated.

$$\bar{v} = \sum_{i=1}^{N} v_i / n \tag{1}$$

$$d_v = \sum_{i=1}^{N} (v_i - \bar{v})^2 / n. \tag{2}$$

The average speed and variance of the vehicles constitute the road traffic feature M_r, and each element contains the road conditions $(r.\bar{v}, r.d_v)$ of a specific road section in a specific time.

5. Road's priority ranking estimation

After feature set X being extracted, in this section, we describe our approach on how to predict the road's priority score to obtain the recommendation ranking. Our approach is motivated by the following two observations: 1) roads, which share similar basic patterns and POI patterns in network, tend to have approximative priority, and 2) roads in similar priority would have the similar feature combination alike to each other in the road network. Therefore, our approach aims to learn the transformation from feature combination to priority score by exploiting the correlations among roads' patterns and the score dependency.

5.1. Variable selection and processing

Firstly, the features set as the independent variables and the dependent variable are determined according to the road traffic characteristics.

Independent variables: Basic features of the road f_r: road length $r.len$, road level $r.lev$, connection number $r.con$, tortuosity $r.tor$. Among them, the road level is a categorical variable, and there are 13 categories in total. To avoid the trap of dummy variables, 12 dummy variables are set to indicate the road level. For example, the highway variable is expressed as $(1,0,0,0,0,0,0,0,0,0,0,0)$. Road POI features $r.f_p$: There are 12 categories of POI, each category is a variable, a total of 12 variables: $r.f_p : r.n_1, r.n_2, r.n_3, r.n_4, r.n_5, r.n_6, r.n_7, r.n_8, r.n_9, r.n_{10}, r.n_{11}, r.n_{12}$.

Therefore, the model selected a total of 27 independent variables.

The dependent variable: According to the definition of the problem, we need to find a suitable concept to express the road recommendation. Cause the speed on the road does not completely satisfy the Gaussian distribution, the road recommendation degree can't be simply expressed with the mean and variance of speed.

Kernel density estimation (KDE) is utilized to estimate the unknown density function in probability theory, which belongs to one of nonparametric test methods. It was proposed by Rosenblatt (1956) and Parzen (1962). We utilize the KDE method to estimate the probability density of speed on each road and calculate the cumulative distribution. We set the road recommendation degree as the speed when the cumulative distribution is p. In experimentation, the value of p is 0.8. Set the recommendation score as the dependent variable of the model.

5.2. Base model

Given the available features of roads' patterns X and the priority score Y, our goal is to find the prediction function:

$$h_\theta(x_1, x_2, \ldots, x_{27}) = \theta_0 + \theta_1 x_1 + \cdots + \theta_{27} x_{27} \tag{3}$$

Assuming $x_0^i = 1 (i \in 1, 2, \cdots, m)$, the hypothesis function of the model can be expressed as:

$$h_\theta\left(x_1, x_2, \cdots, x_{27}\right) = \sum_{i=0}^{27} \theta_i x_i \tag{4}$$

Use the matrix definition to express the hypothesis function more concisely:

$$h_\theta\left(X\right) = [\theta_0 \quad \theta_1 \quad \cdots \quad \theta_{27}] \begin{bmatrix} x_0 \\ x_1 \\ \cdots \\ x_{27} \end{bmatrix} = \theta^{\mathrm{T}} \cdot X \tag{5}$$

If the size of the training set is m, the hypothesis function $h_\theta(X)$ is a vector of $m \times 1$, and θ is a vector of 27×1, and X is a $27 \times m$-dimensional matrix.

General linear regression models usually take the mean square error as the loss function of the model. The algebraic expression of the loss function is as follows:

$$J\left(\theta_1, \theta_2, \cdots, \theta_{27}\right) = \sum_{i=0}^{m} (h_\theta(x_1, x_2, \cdots, x_{27}) - y_i)^2 \tag{6}$$

Next, express the loss function in matrix form:

$$J\left(\theta\right) = \frac{1}{2}(X\theta - Y)^{\mathrm{T}}\left(X\theta - Y\right) \tag{7}$$

The linear correlation makes our model easy to interpret and, moreover, it leads computational efficiency.

5.3. Regularization term $\Omega(\theta)$

We denote the regularization term as $\Omega_{\alpha,\beta}(\theta)$ which aims to capture the intra-correlation of roads' traffic patterns and the dependencies among different scores.

5.3.1. Incorporating roads' similarity

It is easy to understand that a group of objects with similar characteristics are easily clustered with the same label. In order to predict accurately, we hope that the predicted recommendation degrees of roads with similar characteristics will be similar. That is to say, the roads that share similar feature representation should have similar recommendations. Subject to such constraint, we introduce the first part of the regularization to incorporate roads' similarity:

$$\min_{y_i, y_j} \sum_{i,j} s_{i,j} \cdot \left|\left| y_i - y_j \right|\right|_2^2 \tag{8}$$

where $s_{i,j}$ is the function to evaluate the similarity of roads' features between the road u_i and u_j, i.e. the distance between the representation vectors X_i and X_j. We can define the function $s_{i,j}$ in many ways. For simplicity, in this paper, we define $s_{i,j}$ as the cosine similarity, which is estimated as follows:

$$s_{i,j} = \frac{\sum_{m=1}^{M} x_{i,m} \times x_{j,m}}{\sqrt{\sum_{m=1}^{M} \left(x_{i,m}\right)^2} \times \sqrt{\sum_{m=1}^{M} \left(x_{j,m}\right)^2}} \tag{9}$$

$$= \frac{X|i| \times X|j|^{\mathrm{T}}}{\sqrt{X|i| \times X|i|^{\mathrm{T}}} \times \sqrt{X|j| \times X|j|^{\mathrm{T}}}} \tag{10}$$

5.3.2. Incorporating road's recommendation dependency

When studying the relationship between students and scholarships, Guan et al. (2015) find that students with the same labels have similar behavioral characteristics. When studying the spatiotemporal representation learning for driving behavior, Wang et al. (2019) put forward that the trajectories that share similar driving behavior should have close representations in the learned representation feature space. We have the same principle in this work: roads with similar recommendation degrees should have some similar feature combinations. To capture the dependencies among different labels (recommendation degrees), we introduce the second part of the regularization:

$$\min_{y_i,y_j}\sum_{i,j} r_{i,j}\cdot\left|\left|x_i - x_j\right|\right|_2^2 \tag{11}$$

where

$$r_{i,j} = \left|y_i - y_j\right| \tag{12}$$

.The term $r_{i,j}$ is utilized to capture label dependency.

$$\left|\left|x_i - x_j\right|\right|_2 = \sqrt{\sum_{m=1}^{M}\left(x_{i,m} - x_{j,m}\right)^2} \tag{13}$$

$$= \sqrt{X|i| \times X|i|^{\mathrm{T}} + X|j| \times X|j|^{\mathrm{T}} - X|i| \times X|j|^{\mathrm{T}}} \tag{14}$$

which represents the distance of feature values between roads.

After combining these two regularization terms above, we have $\Omega_{\alpha,\beta}(\theta)$.

$$\Omega_{\alpha,\beta}\left(\theta\right) = \alpha\cdot\sum_{i,j} s_{i,j}\cdot\left|\left|y_i - y_j\right|\right|_2^2 + \beta\cdot\sum_{i,j} r_{i,j}\cdot\left|\left|x_i - x_j\right|\right|_2^2 \tag{15}$$

Here, α and β are two trade-off parameters.

5.4. Optimization

Adding the two regularization terms proposed to the basic model, we have a loss function:

$$J\left(\theta\right) = \frac{1}{2}\left(X\theta - Y\right)^{\mathrm{T}}\left(X\theta - Y\right) + \alpha\cdot\sum_{i,j} s_{i,j}\cdot\left|\left|y_i - y_j\right|\right|_2^2 + \beta\cdot\sum_{i,j} r_{i,j}\cdot\left|\left|x_i - x_j\right|\right|_2^2 \tag{16}$$

Since all terms in Eq. 16 are convex, a global solution can be obtained. Generally, linear regression models usually minimize the loss function by gradient descent or least squares optimization methods, and the former method is utilized in this work.

6. Experimental results

In this section, we demonstrate our empirical evaluation of the proposed method (OpRe-RRS) based on real-world ambulances' data collected from Nanjing province in China.

6.1. Data description

Table 1 shows the detailed statistics of our data sets. Generally, our experimental data include two parts, the real rescue data of Nanjing ambulances from June 1st to June 30th, 2016 and the electronic map data of the urban area in Nanjing.

6.1.1. Spatio-temporal data

Spatio-temporal data help us understand people's activity patterns (Li et al., 2020), which is significant to extract ambulance driving patterns. The spatio-temporal data used in this article is the trajectory data of ambulances based on time, derived from the actual response data of ambulances in Nanjing. The data mainly include the ambulance ID, time, real-time latitude and longitude position, real-time direction, real-time speed, and ambulance rescue status. The time records of the ambulances are time data, the real-time latitude and longitude position information and direction are spatial data, and the ambulance ID, speed, and rescue status are attribute information. On average, the ambulance returns location information every 20 s while driving.

Table 1
Statistic of the Experimental Data.

Data Sources	Properties	Statistics
GPS Trajectory	# Ambulances	68
	# Records	1,048,499
	# Features	7
	# Rescue	5,491
	Time Period	06.01.2016–06.30.2016
Road Network	# Roads	96,282
	# Roads Features	10
POI Data	# POIs	33,048
	# Features	10
	# Categories	12

6.1.2. Nanjing electronic map

Nanjing electronic map data mainly includes two parts:

Road network data:

The road database mainly includes road number, category, name, area, latitude and longitude, etc. Road data is accurately classified according to different road levels, and mainly includes the following elements: national highways, provincial highways, expressways, urban expressways, main roads, secondary roads, branch roads, alleys, internal roads in the community, overpasses, viaducts, auxiliary roads, roundabouts, bridges, railways, subways, light rails, etc.

POI data:

POI data includes POI number, category, name, latitude and longitude coordinates and other information. POI categories mainly include party and government agencies, factories and enterprises, hotels, public places (such as libraries, squares, stadiums, children's palaces), shopping centers, catering establishments, educational and scientific research institutions, medical and health care, and transportation service facilities (such as gas stations), transportation hubs, social services (such as photo studios, beauty salons, barber shops, laundry shops), etc.

6.2. Evaluation criteria

Five different evaluation criteria are used to compare the effects of different algorithms. Three are commonly used regression model evaluation indexes: *Mean Absolute Error(MAE)*, *Root Mean Square Error (RMSE)*, R^2 *score*. MAE can well reflect the actual situation of the predicted value error. RMSE can be used to measure the deviation between the observed value and the true value. The coefficient of determination R^2 reflects how much of the fluctuation of y can be described by the fluctuation of x. The larger the value of R^2 is, the higher the degree of explanation of the independent variable to the dependent variable is.

The other two evaluation criteria are indicators used to evaluate the ranking. In the field of *L2R (Learn to Rank)*, in order to evaluate the quality of learning system, researchers have designed a variety of evaluation indicators. Among them, *AP(Average Precision)* can be utilized to evaluate the predicted road priority ranking in this study. By selecting different thresholds, the ranking score can be converted into positive and negative categories, and then classification evaluation indicators such as *Precision* can be calculated. By selecting the score of each sample as the threshold, AP calculates multiple accuracy values, and uses their average value as the index to evaluate the quality of the ranking.

$$AP = \frac{1}{M}\sum_{m=1}^{M} Prec_m \tag{17}$$

The last one is *Ranking Accuracy Rate(RAR)*, which is proposed according to the goal of this article. The goal of the problem in this paper is to sort all the roads by the recommendation degree to maximize the accuracy of sorting. Aiming at the goal, a new evaluation standard *Ranking Accuracy Rate* is set, that is, the ratio of the correct sorting of road sections to the sorting of all road sections. The predicted results are compared in pairs, and every two roads are compared once. If the comparison result is consistent with the original relationship, it is correct, and the inconsistency is wrong. A total of $(n(n-1))/2$ times is compared, and the RAR is the ratio of the correct times to all the comparison times.

$$RAR = TrueRank/AllRank \tag{18}$$

where, *AllRank* is the total number of comparisons between two road sections, and *TrueRank* is the number of road sections that are relatively correct.

6.3. The evaluation on recommendation ranking prediction

To show the effectiveness of our method (OpRe-RRS), we compare our method against other algorithms. Regression is generally used to predict continuous numerical values. Three advanced regression methods are selected as baselines: **Back-ProPagation Network Regression(BP)** (Rumelhart et al., 1986; Wang, 1998), **Support Vector Regression(SVR)** (Drucker et al., 1997; Smola and Schölkopf, 2004) and **Random Forest Regression(RFR)** (Breiman, 2001; Liaw et al., 2002).

After predicting the priority scores of roads, roads need to be sorted, which is also related to *L2R*. In the field of *L2R (Learn to Rank)*, related researchers are consistently improving the ranking model. In this paper, we pay attention to the global ranking results, so we choose a typical ranking method **RankNet** (Burges et al., 2005) as the baseline.

Here, we report our evaluation results of our method (OpRe-RRS) comparing to the baseline algorithms. We show both macro and micro measurements in terms of MAE, RMSE, R^2, RAR and AP in Table 2.

As observed in Table 2, OpRe-RRS is similar to other models in R^2, but the performance of OpRe-RRS is consistently improved in terms of key evaluation indicators RAR and AP. The experimental results further confirm our intuitions, i.e. incorporating the roads' correlation and the priority score dependency into the learning algorithm can indeed improve the predictive performance.

6.4. The discussion on parameters

In Eq. 16, two trade-off parameters α and β are utilized when calculating $J(\theta)$. It is necessary to discuss the influence of these two parameters on the final experimental results. As shown in the Table 3, when α and β are given different values, the different experimental results are obtained.

It can be found from the Table 3 that when α is 0.7 and β is 0.3, the experimental result is similar to other models in R^2, but the performance is consistently improved in terms of key evaluation indicators RAR and AP. That is to say, in Eq. 15, the weights of the first regularization terms in $\Omega_{\alpha,\beta}(\theta)$ should be higher than the other. But the result when α is 0.9 and β is 0.1 is the worst, which confirms that the two parts of $\Omega_{\alpha,\beta}(\theta)$ are both important for predicting the priority of roads.

Table 2
Predictive Performance Comparison.

Method	Evaluation Criteria				
	MAE	RMSE	R^2	RAR	AP
BP	9.2235	12.1094	0.3982	0.7069	0.3829
SVR	9.2337	12.6213	0.3468	0.7112	0.3789
RFR	9.2844	12.6362	0.3656	0.7077	0.3876
RankNet	/	/	/	0.7118	0.3950
OpRe-RRS	**8.4472**	**10.9553**	**0.3998**	**0.7241**	**0.4079**

Table 3
Experimental Results Performance with Different Parameters.

Parameters		Evaluation				
α	β	MAE	RMSE	R^2	RAR	AP
0.1	0.9	9.3991	12.1367	0.3051	0.6798	0.3216
0.3	0.7	8.9329	11.6914	**0.3601**	0.7001	0.3391
0.5	0.5	**8.9314**	**11.5284**	0.3467	0.6941	0.3179
0.7	0.3	9.5343	12.7594	0.3592	**0.7207**	**0.3486**
0.9	0.1	9.5197	12.6538	0.2836	0.6753	0.2836

6.5. Robustness test

The Layout Plan of Pre-hospital Medical First-aid Stations (Points) issued by Nanjing puts forward that the city will add new first-aid stations and strive to have a first-aid station within a service radius of 3-5 km. Ambulances at each station basically only carry out rescue activities in the responsible area, carrying out experiments on road data according to different areas can verify the robustness of the OpRe-RRS model. The difference between the results on MAE, RMSE and R^2 is due to the different numerical ranges of data in different regions, which just shows that it is meaningful for us to recalculate the data in different regions. The results are stable on the key evaluation criteria RAR and AP, which proves that the OpRe-RRS model's robust and can be applied to other cities and regions. See Table 4.

6.6. Applications

Response time for an EMS system is the time interval from the arrival of an emergency call until the ambulance reaches the scene of the incident. For example, having response times of at least 90% of urgent calls below 9 min is a common performance goal in North America (Fitch, 2005). In order to prove the effectiveness of our method, we reselect the routes of the rescue mission, and compare the estimated time.

In our work, the emergency requests are mapped to the vertices, so we only consider to select rescue routes between the vertices and compute such performance measures as the expected travel time. The Dijkstra method (Dijkstra, E.W., 1959) is a well-known algorithm for finding the optimum path in shortest path search problems. The Dijkstra algorithm needs to construct a network topological graph first, and find the shortest path in the order of increasing path's length. We set the road priority as the weight of edge, construct the road network and reroute for each rescue mission. The results show that the estimated time of the re-planned route is **2 min 20 s** less than the original one on average.

In order to further verify the effectiveness of the method(OpRe-RRS) to guide the ambulance route planning method, we conduct a case study to prove the practicability of OpRe-RRS through real examples and data.

As shown in Fig. 3, the continuous blue dots show the real rescue

Table 4
Comparison of Experimental Results in Different Regions.

Regions	Evaluation Criteria				
	MAE	RMSE	R^2	RAR	AP
Xuanwu	9.5343	12.7594	0.3592	0.7207	0.3486
Jianye	11.6700	14.3715	0.2820	0.6835	0.3576
Gulou	7.2942	9.7915	0.2126	0.6618	0.3349
Qinhuai	7.8664	10.9994	0.2774	0.6692	0.3095

Fig. 3. An Example of Selecting Rescue Routes Based on the Model Results.

route trajectory of an ambulance. It takes 23 min for the ambulance to travel from the emergency center A to the destination B. Re-planning the rescue route of this ambulance by using the above road recommendation ranking results, as shown in the red solid line in the figure. In order to make the calculation results more accurate and practical, the average speed of the road section is utilized as the speed of the ambulance to calculate the rescue time of the original route and the recommended route, which are **22 min 11 s** and **19 min 20 s**, respectively.

The actual rescue time of the original route is not much different from the time calculated by the average speed, which proves that it is meaningful to compare the rescue time by calculating the time by the average speed of the road section. According to the result of the re-planned route, compared with the original route, the forecast duration is significantly shortened.

In the ambulance rescues, one more second means more hope in life. Through real examples, we prove that the method proposed in this paper can effectively shorten the rescue time of ambulances.

7. Conclusion

The demand of first aid is dynamic and time-varying. The ambulance route recommendation strategy(OpRe-RRS) can realize the optimization of the emergency response level under the limited level of rescue resources.

In this paper, our main task is to sort the priority of roads. This sorting can be applied to the navigation system as a factor considered in route recommendation together with other factors such as the length of the road and the real-time traffic flow. This preferentially selects high-priority roads for ambulances, which can effectively shorten the rescue time of ambulances. The conclusions are of great significance for pre-hospital emergency activities, and help utilize the most cost-effective methods to increase the speed of ambulances. At the same time, ambulance drivers can also be trained to enhance their understanding of the road, and they can choose a relatively optimal route when making independent choices. In addition, the recommended order of roads obtained in this paper also has a certain reference significance for the government's road planning and urban planning.

Finally, this article has room for improvement. Some features such as traffic around the road, traffic lights at intersections, road flatness are not considered in this paper. At the same time, the priority of road may be related to its upstream and downstream roads, but we don't consider the relationship between roads. Therefore, the future research can expand on the basis of this article for more rational physical attributes and consider roads' topology.

CRediT authorship contribution statement

Xiaolin Li: Methodology, Writing - review & editing. **Xiaotong Niu:** Writing - review & editing. **Guannan Liu:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Alanis, R., Ingolfsson, A., Kolfal, B., 2013. A markov chain model for an ems system with repositioning. Prod. Oper. Manage. 22 (1), 216–231.

Balcik, B., Silvestri, S., Rancourt, M., Laporte, G., 2019. Collaborative prepositioning network design for regional disaster response. Prod. Oper. Manage. 28 (10), 2431–2455.

Benabdouallah, M., Bojji, C., Yaakoubi, O.E., 2016. Deployment and redeployment of ambulances using a heuristic method and an ant colony optimization case study. In: 2016 Third International Conference on Systems of Collaboration (SysCo), pp. 1–4.

Blanger, V., Ruiz, A., Soriano, P., 2019. Recent optimization models and trends in location, relocation, and dispatching of emergency medical vehicles. Eur. J. Oper. Res. 272 (1), 1–23.

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32.

Burges, C., Shaked, T., Renshaw, E., Lazier, A., Deeds, M., Hamilton, N., Hullender, G., 2005. Learning to rank using gradient descent. In: Proceedings of the 22nd international conference on Machine learning, pp. 89–96.

Chen, A.Y., Lu, T., Ma, M.H., Sun, W., July 2016. Demand forecast using data analytics for the preallocation of ambulances. IEEE J. Biomed. Health Inf. 20 (4), 1178–1187.

Cherkesly, M., Rancourt, M., Smilowitz, K.R., 2019. Community healthcare network in underserved areas: design, mathematical models, and analysis. Prod. Oper. Manage. 28 (7), 1716–1734.

Degel, D., Wiesche, L., Rachuba, S., Werners, B., 2015. Time-dependent ambulance allocation considering data-driven empirically required coverage. Health Care Manage. Sci. 18 (4), 444–458.

Dijkstra, E.W., 1959. A note on two problems in connexion with graphs. Numerische Mathematik 269–271.

Drucker, H., Burges, C.J.C., Kaufman, L., Chris, J.C., Kaufman, B.L., Smola, A., Vapnik, V., 1997. Support vector regression machines. Adv. Neural Inf. Process. Syst. 28 (7), 779–784.

Erkut, E., Ingolfsson, A., Erdoan, G., 2008. Ambulance location for maximum survival. Naval Res. Logist. 55 (1), 42–58.

Fitch, J., 2005. Response times: myths, measurement & management. JEMS 30 (9), 47–56.

Gendreau, M., Laporte, G., Semet, F., 2006. The maximal expected coverage relocation problem for emergency vehicles. J. Oper. Res. Soc. 57 (1), 22–28.

Greenfeld, J.S., 2002. Matching gps observations to locations on a digital map. In: 81th annual meeting of the transportation research board. vol. 1. pp. 164–173.

Guan, C., Lu, X., Li, X., Chen, E., Zhou, W., Xiong, H., 2015. Discovery of college students in financial hardship, in: Proceedings of the 2015 IEEE International Conference on Data Mining (ICDM). ICDM '15. p. 141–150.

Jagtenberg, C., Bhulai, S., van der Mei, R., 2015. An efficient heuristic for real-time ambulance redeployment. Oper. Res. Health Care 4, 27–35.

Jiang, Z., Liu, Y., Fan, X., Wang, C., Li, J., Chen, L., 2020. Understanding urban structures and crowd dynamics leveraging large-scale vehicle mobility data. Front. Comput. Sci. 14(5).

Ji, S., Zheng, Y., Wang, Z., Li, T., 2019. A deep reinforcement learning-enabled dynamic redeployment system for mobile ambulances. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 3, 1–20.

Liaw, A., Wiener, M., et al., 2002. Classification and regression by randomforest. R News 2 (3), 18–22.
Li, Y., Zheng, Y., Ji, S., Wang, W., Gong, U.L.H., 2015. Location selection for ambulance stations: a data-driven approach. In: Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems. SIGSPATIAL '15. Association for Computing Machinery.
Li, X.-L., Ma, L., He, X.-D., Xiong, H., 2020. You are how you behave – spatiotemporal representation learning for college student academic achievement. J. Comput. Sci. Technol. 35, 353–367.
Liu, G., Qu, J., Li, X., Junjie, W., 2020. Dynamic ambulance redeployment based on deep reinforcement learning. J. Manage. Sci. China 23 (2), 39–53.
Parzen, E., 1962. On estimation of a probability density function and mode. Ann. Math. Stat. 33 (3), 1065–1076.
Rosenblatt, M., 1956. Remarks on some nonparametric estimates of a density function. Ann. Math. Stat. 27 (3), 832–837.
Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning representations by back-propagating errors. Nature 323 (6088), 533–536.
Schmid, V., 2012. Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. Eur. J. Oper. Res. 219 (3), 611–621 feature Clusters.
Shang, J., Zheng, Y., Tong, W., Chang, E., Yu, Y., 2014. Inferring gas consumption and pollution emission of vehicles throughout a city. In: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '14. Association for Computing Machinery, pp. 1027–1036.
Smola, A.J., Schölkopf, B., 2004. A tutorial on support vector regression. Stat. Comput. 14 (3), 199–222.
Talarico, L., Meisel, F., Srensen, K., 2015. Ambulance routing for disaster response with patient groups. Comput. Oper. Res. 56, 120–133.
van Barneveld, T., 2016. The minimum expected penalty relocation problem for the computation of compliance tables for ambulance vehicles. INFORMS J. Comput. 28 (2), 370–384.
van Buuren, M., Jagtenberg, C., van Barneveld, T., van der Mei, R., Bhulai, S., 2018. Ambulance dispatch center pilots proactive relocation policies to enhance effectiveness. INFORMS J. Appl. Anal. 48 (3), 235–246.
Wang, S., 1998. An insight into the standard back-propagation neural network model for regression analysis. Omega 26 (1), 133–140.
Wang, D., Xie, G., Ning Ye, et al., 2006. Constructing of modern pre-hospital emergency system. Chin. Hospital Manage. 26(9), 45–46.
Wang, P., Li, X., Zheng, Y., Aggarwal, C., Fu, Y., 2019. Spatiotemporal representation learning for driving behavior analysis: a joint perspective of peer and temporal dependencies. IEEE Trans. Knowl. Data Eng. pp. 1–1.
Zhou, Z., Matteson, D.S., 2015. Predicting ambulance demand: a spatio-temporal kernel approach. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '15. Association for Computing Machinery, pp. 2297–2303.