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Optimal Path Selection for Multi-weight Logistics Combined With High-dimensional Deep Learning Algorithms

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Abstract

The optimal path selection technology of multi-weight logistics combined with high-dimensional deep learning algorithms can effectively solve the cost problems that lead to the cumbersome delivery process. Other solutions to the logistics path (such as management) cannot effectively solve this problem. The successful development of the optimal path selection of multi-weight logistics extends the distribution path to each city, uses high-dimensional deep learning algorithms to establish models, determines the optimal path of multi-weight logistics, and achieves cost control.

Keywords: *Logistics, Optimal Path, High-dimensional Deep Learning Algorithm, Simple Path;*

1. Introduction

The rapid development of the Internet economy has improved the logistics system from sales, purchases, finance and distribution[1-3]. Distribution centers have also entered tens of thousands of households, and if logistics distribution wants to stand out in the rapidly developing external environment, it must increase the circulation speed of goods on an inherent basis and also need to control costs with sufficient control. Then the development of logistics Become inevitable[4-6]. The integration of high-dimensional deep learning algorithms and the combination of computers optimizes the distribution path of logistics and greatly improves the cost and time. This paper establishes a multi-objective model based on high-dimensional deep learning algorithms to find the optimization of multi-weight logistics paths.

2. The first k simple shortest path problem

Given a directed graph (DG, directed graph) G=(V,E), the number of vertices n=|V|, the number of edges r=|E|, there is no negative weight edge in G, and then a positive integer is given k and the two vertices s and t, find the first k shortest paths from s to t in ascending order. In the first k shortest path problems, what we are looking for is not just one path, but multiple paths, and these multiple optimal paths are arranged in ascending order. The first k shortest path problems can be divided into two categories: simple constraints and no simple constraints. The so-called simple path refers to a path that does not contain a circle, that is, a path that cannot be repeated. The following figure illustrates the difference between the first k shortest paths and the first k simple shortest paths:

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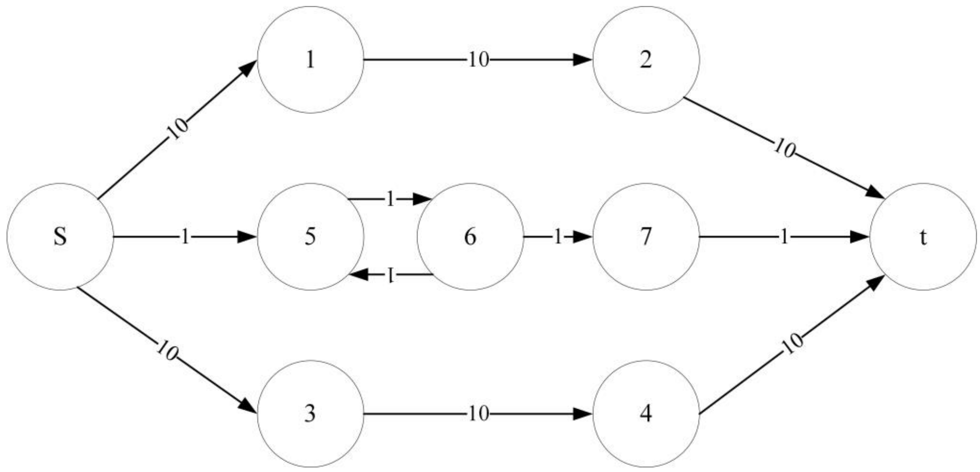

Figure 1. The difference between the first k shortest paths and the first k simple shortest paths.

As can be seen from the above figure, the lengths of the first three simple shortest paths are 4, 30 and 30 respectively. The three shortest paths without simple constraints are 4, 6 and 8, and there can be cycles (5, 6, 5) in the path. It can be seen that although in a graph with non-negative weights, the shortest path is always a simple path, there may be cycles in the second, third... shortest paths.

The time complexity of this algorithm is also O(kn(m+nlogn)). According to the experimental results of John Hershberger et al., in most cases, this algorithm is faster than Yen's algorithm. However, as John Hershberger et al. pointed out in their paper, in the case of directed graphs, their alternative path algorithm sometimes fails, but such failures are easy to detect. Once the alternative path algorithm fails, use other alternative path algorithms in this round.

This topic focuses on the first k simple shortest paths, which are inseparable from the optimization criteria of logistics.

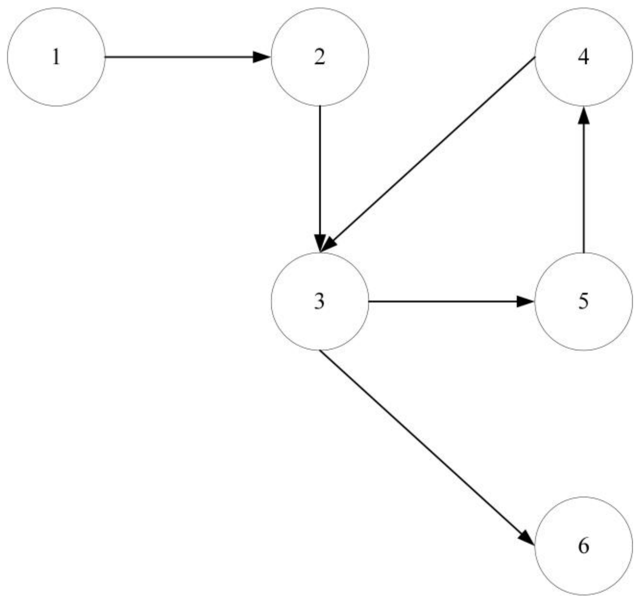

Figure 2. The i-th shortest path with a circle.

In Figure 2, assuming that the optimization goal is distance, the first shortest path from point 1 to point 6 without simple constraints is: Path A={e<1,2>,e<2,3>,e<3, 5>,e<5.4>,e<4,3>,e<3,6} Since point 3 has been passed twice, obviously this is a circled path. After deleting the edges e<3,5>, e<5.4> and e<4,3>, we get a simple path Path B={e<1,2>,e<2,3>,e<3,6 >}. It is easy to prove that the length of Path B is less than the length of Path A, that is, Path B is one of the shortest paths (i-1) from point 1 to point 6, and Path A is the i-th shortest path from point 1 to point 6. . Not only from the perspective of distance, Path B is better than Path A, that is, from the perspective of time or cost, Path B is

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also better than Path A, because all the road sections Path A in Path B pass. It can be seen that after we find Path B, there is no need to find Path A again. For this reason, we mainly focus on the first k shortest paths with simple constraints.

Make the following assumptions about the model:

(1) Items are only processed at logistics nodes.

(2) Only one node at the same level that provides similar logistics services can be selected.

(3) Only one path can be selected among several paths existing between adjacent nodes.

(4) There is no path connection between nodes at the same level.

The description of model variables is shown in formulas (1) and (2):

$$x_{v,v+1}^{i}=\begin{cases}1, & \textit{Choose the } i-th \textit{ path between nodes } v \textit{ and } v+1\\ 0, & \textit{otherwise}\end{cases} \tag{1}$$

$$y_{v}=\begin{cases}1, & \textit{Choose to carry out logistics processing activities at node } v\\ 0, & \textit{otherwise}\end{cases} \tag{2}$$

Among them, $c_{v,v+1}^{i}$ is the unit transportation cost between node v and v+1; q is the volume of logistics in the logistics chain; $l_{v,v+1}^{i}$ is the length of the ith path between node v and v+1; rv is the logistics at node v The unit processing cost of the processing activity; V is the set of available logistics nodes; I is the set of available logistics routes.

3. Implementation method of multi-objective optimal path under high-dimensional deep learning algorithm

For the high-dimensional deep learning algorithm multi-objective optimal path problem between two points in the distribution center, the following three methods can be used:

Method 1: The singularization of road section weights. This method assigns a single fixed weight to each section, but this weight not only considers the distance, not only the time, but also considers a variety of factors. Then use the comprehensive weight as the key target weight, call the shortest path algorithm between the two points, and use the obtained shortest path as the optimal path. It is worth pointing out that how to calculate the comprehensive weight of the road segment is a problem worth exploring for this method.

Method 2: Use a certain target weight of the road segment as the key target weight to find the first k simple shortest paths between two points. Then calculate the target weights of the k paths. For example, three weights are assigned to each road section of the directed graph, and the three weights represent the distance of the road section, the travel time of the road section, and the travel cost of the road section. We use the distance of the road segment as the target weight to find the first k shortest paths, and then calculate the distance, travel time and travel cost of the first k shortest paths. The user can select a path from the first k paths as the optimal path for each target weight of the integrated path according to their actual needs.

Method 3: Each target weight of the road segment is used as the key target weight in turn, and the first k simple shortest paths are respectively calculated. If each road section has m target values, then mk paths can be obtained and then the target weights of these

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mk paths are calculated. The user can select a path from the previous mk paths as the optimal path according to the target weights of the comprehensive path according to their actual needs. Assuming that three weights are assigned to each road section of the directed graph, the three weights represent the distance of the road section, the travel time of the road section and the travel cost of the road section respectively, and the distance, travel time and travel cost of these 3k paths can be obtained.

Method 1 is not only simple in algorithm, but also the shortest path given is the optimal path. However, when assigning value, it is a comprehensive assignment. Because the unit of each target weight is different, the relationship function between the comprehensive weight and each target weight is difficult to determine. Moreover, the needs of customers are diverse. Different customers and different times have different needs. The fixed coefficient is obviously not in line with reality. This kind of algorithm relies more on the customer's experience, and sometimes requires the user to constantly adjust the relationship function between the comprehensive weight and each target weight based on the feedback information.

Method 2 and Method 3 respectively give k and mk optimal simple paths according to the target weight of the road section, and give the weights associated with each path. The algorithm is reasonable and convincing, and which one? It is that the optimal path in the mind of the user is not given by the algorithm, but the user makes his own choice based on the calculation result.

But method two and method three are still different. Method two uses only one target weight of the road segment as the key target weight to find alternative paths, while method three treats each target weight of the road segment equally, making full use of existing data. Furthermore, suppose that the customer requires y alternative paths. Method 2 must use a certain target weight value to find the first y simple shortest paths, while method 3 only needs to calculate m times before ([y/m]+l) simple shortest paths ([y/m] represents the largest positive integer not exceeding y/m). In the algorithm, the above method two has more complicated time complexity than the method three.

In the actual logistics distribution, eight to nine alternative routes can already meet the needs of users. If each road section has three target weights, nine alternative paths are required. As long as these three target weights are used as key target weights to find the first three simple shortest paths, we can. A total of three (first) shortest paths, three second simple shortest paths, and three third simple shortest paths are calculated.

4. Algorithm implementation and results

We choose method three here to realize the optimal path between the two points of the distribution center. For the logistics chain, a simple network structure of the starting point 0 and the ending point D of logistics activities, and the first-level intermediate nodes are given. Each level has two intermediate nodes that provide the same service. There is no path connection between nodes of the same level, and there are two paths between any two nodes of adjacent levels, as shown in Figure 3.

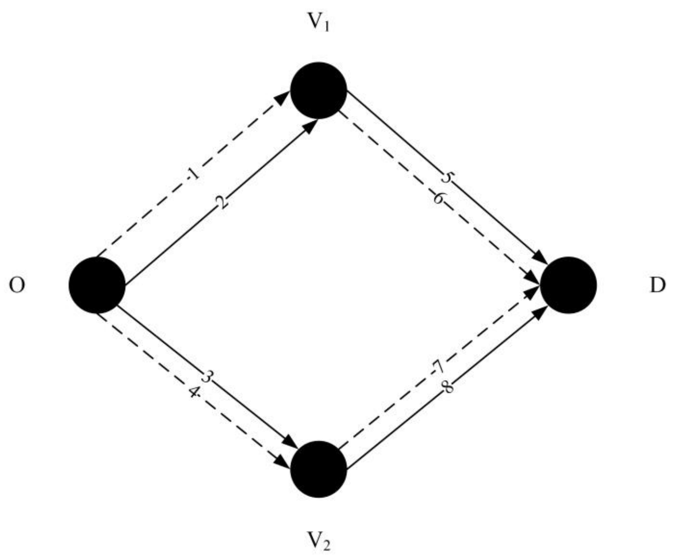

Figure 3. The prototype network of the logistics chain.

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Obviously, for the logistics chain from 0 to D, there are logistics nodes v1, v2, and logistics paths 1 to 8 that can provide the same service. Logistics processing activities on v1 and v2 will incur costs like the logistics route. Therefore, when choosing the shortest path from 0 to D in the logistics chain, in addition to the path, the node must be selected, and the cost of the node and the path must also be considered.

To solve this problem, relying on method three to solve the optimal logistics chain selection problem with weighted nodes in multiple graphs, the basic idea is to require that there are no multiple edges in the network, and only edges have rights. At this time, virtual intermediate nodes and Edge, decompose the intermediate nodes that have multiple edges to reach, so that the edge between each pair of adjacent nodes is unique, and each virtual node can correspond to the next level edge connected to the node in the prototype network of the node , Convert multiple graphs into simple graphs. At the same time, we use the idea of roulette to decompose the weights on the original nodes, and assign the decomposed values to the edges of the simple graph. At this time, the logistics chain prototype network with multiple sides is transformed into a logistics chain transformation network with a simple graph structure.

Then the problem after conversion is described as: there is a type of logistics activity from the starting point 0 to the end point D, passing through M-level logistics nodes, there is no path connection between the same level logistics nodes, and determining the best logistics node and logistics path combination method, so that the total The lowest cost.

4.1 Data source and program operating environment

The road image comes from a map of a Chinese city on OSM. We selected 83 points and 288 road segments, and processed the respective target weights of each road segment. The processing results made each road segment have four values: the length of the road segment, the road segment's toll cost, and the average value of the road segment's transit time. variance. Here, the length of the road segment and the cost of the vehicle passing a certain road segment are taken as fixed values, and the time for the vehicle to pass a certain road segment is a normal random variable. The first three simple shortest paths are obtained by taking turns as the key target value of the length of the road section, the cost of the road section and the average value of the road section traveling time. This topic assumes that the travel time of each road is irrelevant. This is convenient for estimating the variance of the travel time of each path after obtaining the nine paths.

4.2 Result analysis

This program can calculate the first 3 shortest paths under each target weight between any two points in the graph, and output a total of 9 paths.

The program not only gives 9 paths, but also gives the path length, transit cost, mean value and variance of transit time of each path. In order to facilitate the user's path selection, we draw the program's running results into a table (see Table 4):

In the path target weight information table, although nine alternative paths are given, many paths are repeated. For example, the shortest distance path, the shortest path with transit cost, and the second simplest shortest path with mean transit time are the same path. In the final result processing, it is of course possible to treat these three alternative paths as one path. If there are m weights for each road segment, and the first k simple shortest paths are calculated for each weight, then alternative paths can be obtained. When the same alternative paths are merged, the final number of alternative paths can be obtained Between k and mk.

Different users have different first, second, and third goals. According to the difference of the first goal, the final alternative paths are listed in the following tables, as shown in Table 1, Table 2, and Table 3:

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Table 1. Path target weight information table.

key target weight	Path	Path length (m)	Traffic cost (minutes)	Average transit time (seconds)	Variance of transit time (seconds ^{2})
Path length	Path1	4084	735	690	1075
	Path2	4115	740	691	1157
	Path3	4126	733	697	1081
Toll cost	Path1	4084	735	689	1075
	Path2	4126	733	697	1081
	Path3	4155	740	691	914
Mean transit time	Path1	4115	740	691	1157
	Path2	4084	735	689	1077
	Path3	4126	733	697	1081

Table 2. Final path target weight information table (the path length is the first target).

Path	Path length (m)	Traffic cost (minutes)	Average transit time (seconds)	Variance of transit time (seconds ^{2})
Path1	4084	735	690	1075
Path2	4115	740	691	1157
Path3	4126	733	697	1084
Path4	4157	744	699	914

Table 3. Final path target weight information table (traffic cost is the first target).

Path	Traffic cost (minutes)	Path length (m)	Average transit time (seconds)	Variance of transit time (seconds ^{2})
Path1	735	4084	690	1075
Path2	733	4126	697	1081
Path3	740	4115	691	1157

Path4	744	4157	699	914

Table 4. Final path target weight information table (the average transit time is the first target).

Path	Average transit time (seconds)	Variance of transit time (seconds ^{2})	Path length (m)	Traffic cost (minutes)
Path1	690	1157	4115	740
Path2	691	1075	4084	735
Path3	697	1081	4126	733
Path4	699	914	4157	744

Since different key target weights have path duplication on the first k simple shortest paths, although there are mk candidate paths initially obtained, there are few final candidate paths. In order to increase the number of final alternative paths, so that users can consider more non-quantitative factors in the final decision, when the number of final alternative paths is small, we can increase the number of k while keeping m unchanged. So that the final output number of candidates meets the needs of users.

5. Conclusion

This paper analyzes the optimal path selection of high-dimensional deep learning multi-weight logistics path, and establishes a multi-objective path model; in the established problem model, proposes a method to solve the problem, and the multi-weight logistics optimization algorithm path is small and alternative More paths.

References

1. Liu B, Tang J, Li Z, et al. Optimal selection of sewage treatment technologies in town areas: a coupled multi-criteria decision-making model [J]. Environmental Management, 2020, 5(4): 102-110.
2. Thraves Caro C, Doncel J, Brun O. Optimal path discovery problem with homogeneous knowledge [J]. Theory of computing systems, 2020, 64(2): 227-250.
3. Basciani F, D'Emidio M, Ruscio D D, et al. Automated selection of optimal model transformation chains via shortest-path algorithms [J]. IEEE Transactions on Software Engineering, 2020, 46(3): 251-279.
4. Gu Q, Wang R. Evaluation path selection of opening-up level of chinese coastal cities based on entropy weight-topsis-grey correlation: from researches on ten coastal cities [j]. journal of coastal research, 2020, 115(1): 636-641.
5. Meoni F, Carricato M. Optimal selection of the motor-reducer unit in servo-controlled machinery: A continuous approach [J]. Mechatronics, 2018, 56(4): 132-145.
6. Yablochkin E, Cukurel B. Selection of optimal multi-hotwire probe in constant temperature anemometry (CTA) for transonic flows [J]. Experiments in Fluids, 2019, 60(2): 1-8