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Optimization of Logistics Cargo Tracking and Transportation Efficiency based on Data Science Deep Learning Models

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Abstract: With the digital transformation of the logistics industry, smart logistics algorithms have become a core technology to improve efficiency and reduce costs. This paper reviews the development history of traditional logistics technology and discusses the key role of technologies such as the Internet of Things, big data analysis, artificial intelligence, and automation in logistics technology innovation. It focuses on the application of intelligent logistics algorithms in path optimization, intelligent scheduling, data mining and prediction, and intelligent warehousing. To solve the problem of inconsistency between training and testing objectives, this paper proposes DRL4Route, a deep reinforcement learning-based path optimization framework, and designs the DRL4Route-GAE model. Validated through extensive offline experiments and online deployments, the model significantly outperforms existing optimal benchmark methods on real datasets, improving the location deviation squared metrics and the top-three location prediction accuracy metrics. These research results provide important support to further promote the intelligent development of the logistics industry.

Keywords: Intelligent logistics algorithms; path optimization; deep reinforcement learning; data mining; transport efficiency optimization

1. Introduction

With the digital transformation of the logistics industry, intelligent logistics algorithms have become a core technology for improving efficiency and reducing costs. By leveraging advanced technologies such as Big Data and Artificial Intelligence, logistics companies can optimize logistics data for intelligent decision-making and efficient operations [1]. Intelligent logistics algorithms play a key role in several ways. Firstly, in terms of route planning, these algorithms can significantly reduce transport time and costs and improve transport efficiency. Secondly, through demand forecasting and inventory management, intelligent logistics algorithms can optimize supply chain management by reducing inventory costs and the risk of stock-outs.

In addition, real-time monitoring of logistics links and quick response to abnormal situations is another important function of intelligent logistics. This not only improves the flexibility and resilience of the logistics system but also enables more efficient resource utilization in terms of resource allocation. Accurate prediction of logistics demand is also a major advantage of intelligent logistics algorithms, enhancing customer experience and satisfaction. Intelligent route planning and demand forecasting algorithms serve as important examples, significantly improving transport efficiency and inventory management efficiency.

Overall, intelligent logistics algorithms play a crucial role in improving efficiency, reducing costs, and enhancing customer experience. This paper aims to explore strategies and methods for

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optimizing logistics cargo tracking and transport efficiency based on data science and deep learning models, to further promote the intelligent development of the logistics industry.

2. Related Work

2.1. Traditional Logistics Technologies

With the acceleration of digital transformation and the rise of the smart logistics era, logistics technology innovation has emerged. Digital transformation enables companies to achieve a fundamental shift in their business model through digital technologies, which greatly enhances the efficiency and accuracy of the logistics process [2]. In this, the availability of real-time data and collaboration between supply chain segments are key to logistics technology innovation. For example, real-time collaboration mechanisms in digital platforms enable the sharing of supply chain information and improve overall operational efficiency.

Looking back at traditional logistics technology, historical data shows that logistics companies in the late 20th century mainly relied on manual records and basic computer systems to manage transport and inventory. Under this model, information transfer is slow and error-prone, leading to inefficiency [3]. With the development of information technology, barcode and radio frequency identification (RFID) technologies were widely used in the late 20th and early 21st centuries, significantly improving the efficiency of logistics data collection and processing. Since then, the introduction of Electronic Data Interchange (EDI) systems has made the transmission of information in all segments of the supply chain faster and more accurate, promoting the modernization of logistics management.

Entering the 21st century, the advent of the intelligent logistics era has promoted the further development of logistics intelligence. In this, the application of advanced technologies such as artificial intelligence and the Internet of Things is an important direction of logistics technology innovation. Intelligent decision-making and automation have become the core features of the intelligent logistics era. For example, Amazon optimizes the transport path with its intelligent path planning system and realizes intelligent inventory management, which significantly reduces logistics costs and improves transport efficiency [4]. In addition, the development of emerging technologies has also brought new opportunities for logistics technology innovation. Blockchain technology provides a more secure and transparent data exchange for the logistics industry through its decentralization and data tampering characteristics. Edge computing pushes computing to where the data is generated, which in turn improves real-time monitoring efficiency and real-time performance. The application of these technologies not only improves the efficiency and reliability of logistics operations but also brings a new business model and service experience.

In summary, traditional logistics technology is in the continuous development and evolution of the gradual transformation to intelligence [5]. The introduction of barcode, RFID, EDI, and other technologies has laid a solid foundation for the logistics industry, while the application of emerging technologies such as artificial intelligence, the Internet of Things, blockchain, and edge computing has injected new vitality into logistics technological innovation and promoted the sustainable development of the logistics industry. This series of technological advances and innovations reflects the huge potential and infinite possibilities of the logistics industry in the context of the digital era.

2.2. AI-Drives Logistics Technology Innovation

Logistics technology innovation is driven by a variety of technologies, of which IoT, big data analytics, artificial intelligence, and automation are the most critical factors. IoT technology enables real-time monitoring of logistics processes by connecting devices and sensors, providing data support for intelligent decision-making. For example [6], IoT temperature monitoring systems ensure the safety of perishable goods during transport by tracking the temperature of goods in real time. According to McKinsey's report, enterprises applying IoT technology can increase efficiency by 10-15 percent in logistics operations.

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Big data technology also plays an important role in logistics technology innovation. By processing and analyzing massive amounts of data, logistics companies can conduct predictive analysis and real-time monitoring. Big data technology can use historical data to predict market demand, thereby optimizing transport plans and identifying and dealing with problems in real-time in the logistics chain. For example, big data-driven demand forecasting systems enable logistics companies to more accurately predict market demand and improve supply chain efficiency [7]. According to a DHL study, the application of big data analytics can increase forecast accuracy by 20-30 percent, thereby significantly reducing inventory costs and transport expenses.

Artificial Intelligence (AI) plays a crucial role in logistics technology innovation. Intelligent path planning and automated decision-making are important applications of AI technology in logistics. By optimizing transport paths through machine learning, logistics companies can significantly improve transport efficiency [8,9]. The application of deep learning technology, on the other hand, realizes automated decision-making and further enhances operational efficiency. For example, a machine learning-based cargo loading optimization system improves vehicle loading efficiency and reduces transport costs through intelligent algorithms. Studies have shown that the transport efficiency of logistics companies can be increased by 25 percent with the application of an intelligent route planning system.

The application of automation technology reduces the reliance on manual intervention and improves operational efficiency. Automated equipment enables rapid storage and picking of goods in warehouses, and automated driving technology promotes the development of driverless vehicles, thus improving transport efficiency and safety [10]. For example, Amazon's automated warehouse picking robots have been widely used in its warehouse centers, significantly reducing operational costs and improving picking efficiency. According to The Economist, automated warehouse systems can increase operational efficiency by 30-40 percent.

The integration and application of these key technologies have greatly promoted the innovation of logistics technology, improved the overall efficiency of the logistics industry, and provided strong support for digital transformation. By combining IoT, big data, artificial intelligence, and automation technologies, logistics companies can realize a full range of intelligent and automated operations, thereby maintaining a leading position in the fiercely competitive market. Actual data and literature reviews show that with the continuous development and improvement of these technologies, the logistics industry will usher in a more efficient, safe, and intelligent future.

2.3. Intelligent Logistics Algorithms

Intelligent logistics algorithms are based on sensing technology and data processing. Sensing technology ensures real-time data collection and data processing transforms the data into valuable information that provides the basis for the algorithm [11]. The importance of sensing technology is reflected in three aspects: real-time data acquisition, sensors capture the location of goods, temperature and humidity, vehicle status, and other data to provide a transparent view; environmental monitoring, such as temperature sensors to ensure the quality of cold chain logistics goods; location tracking, GPS real-time tracking of goods and vehicle location, optimize path planning, to ensure on-time delivery. The importance of data processing lies in big data analysis, which reveals patterns and trends in the logistics process and provides support for decision-making; real-time decision support, which handles real-time data, provides feedback to the logistics system, and responds quickly to a variety of conditions; and predictive analyses, which combines historical and real-time data to anticipate future demand and plan the system. The combination of sensing technology and data processing provides the cornerstone for intelligent logistics algorithms. Sensing technology provides raw data, data processing transforms it into useful information, and together they optimize the logistics system to improve efficiency and intelligence.

1. Path optimisation algorithm

The path optimization algorithm is a key technology in graph theory and network analysis, aiming to find the optimal or shortest path in a given network [12]. Dijkstra and A star algorithms are famous shortest path algorithms, and genetic algorithms show innovative applications in path

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planning with the principle of biological evolution. Dijkstra's algorithm is based on the greedy strategy, which is suitable for the single-source shortest path problem of the weighted directed graph. It starts from the starting node and gradually expands the node with the shortest distance until it reaches the target node, and constantly updates the distance information of neighboring nodes to ensure that the shortest path is found. Compared to Dijkstra's algorithm, A star algorithm combines the advantages of global search with heuristic information. The estimated cost to the target node guides the search direction and improves the search efficiency. A star algorithm maintains a priority queue, selects the node with the smallest estimated cost for expansion, and updates the estimated cost of neighboring nodes in real time to find the shortest path quickly [13]. Genetic algorithms are applied to path planning to reflect the power of natural selection and genetic evolutionary principles. By defining the path encoding and fitness function, the initial path solution population is randomly generated, the crossover and mutation operations produce new path solutions, and the excellent individuals are selected for reproduction according to the fitness function, and the iteration continues until the stopping condition is satisfied, and the globally optimized path is obtained. Taking urban map path planning as an example, Dijkstra's algorithm finds the shortest path between two nodes, A star algorithm introduces heuristic information to improve the search efficiency, and a genetic algorithm plays an advantage in complex network or large-scale path planning to search globally and get a better solution.

2. Intelligent Scheduling Algorithm

Intelligent scheduling algorithms refer to the optimization of resource allocation and task scheduling to significantly improve the efficiency of logistics, commonly used methods include genetic algorithm, simulated annealing algorithm, and ant colony algorithm. Genetic algorithms simulate the genetic evolution process in nature and explore the optimal solution through crossover and mutation operations in the population. In logistics scheduling, genetic algorithms can optimize vehicle paths and cargo loading to minimize total distance traveled or maximize resource utilization. The simulated annealing algorithm, on the other hand, draws on the annealing process in metal smelting to jump out of the local optimum by accepting inferior solutions with a certain probability. In logistics scheduling, it helps in a global search to optimize distribution routes or task scheduling orders. The ant colony algorithm is inspired by the foraging behavior of ant colonies and guides the search process through pheromone release and update. In logistics scheduling, it optimizes distribution routes and simulates cooperative driving between vehicles. The strengths of these algorithms are global search capability, adaptability, and ability to handle complex problems.

3. Data Mining and Predictive Logistics Algorithms

Data mining and predictive logistics algorithms are crucial in modern logistics management. They explore data associations, reveal time series patterns, and use machine learning to provide powerful prediction and optimization tools for logistics [14]. Association rule mining identifies item correlations in datasets to optimize inventory layout and joint distribution. For example, frequently co-occurring products intelligently adjust storage locations or combine shipments to improve efficiency. Time series analysis forecasts demand, transit time, and inventory movements. Analyse historical data to gain insight into seasonal trends, cyclical fluctuations, and other factors affecting logistics, providing more accurate planning and adjustment. Machine learning analyses historical sales data to predict future demand, optimize inventory management, and reduce the risk of stock-outs. Optimise transport routes taking into account traffic, weather, and other factors to improve delivery efficiency and identify supply chain risks. Data mining and predictive logistics algorithms improve logistics operation efficiency, reduce costs, provide more accurate forecasts, and enhance supply chain competitiveness.

4. Intelligent Warehousing Algorithms

Intelligent warehousing algorithm is a key technology of modern logistics, which significantly improves warehousing efficiency by integrating advanced technologies and algorithms. Cargo distribution algorithms and intelligent storage rack systems are some of the core applications. Cargo distribution algorithms optimize the flow of goods and picking in the warehouse [15]. Optimal path planning ensures that goods move quickly and efficiently, taking into account cargo relationships,

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shelf locations, and real-time traffic conditions. Intelligent picking systems use machine learning to predict picking sequences, reducing picking time and improving accuracy. Dynamic scheduling assigns tasks based on real-time demand to maximize resource utilization, including task allocation for automated equipment. Intelligent storage rack systems enhance storage and monitoring capabilities through automation and intelligent technologies. Automation technologies such as robots and automated lifting tables enable automated storage and retrieval, reducing manual handling and increasing speed and accuracy. Algorithms optimize warehouse layout to maximize space, reduce costs, and increase storage density. Real-time monitoring systems monitor goods on the shelves with sensors to ensure inventory accuracy and detect and respond to anomalies promptly. Intelligent warehousing algorithms improve warehouse efficiency, reduce manual errors, lower inventory costs, shorten order processing time, and improve customer satisfaction.

3. Methodology

Learning-based approaches have been used to solve collection and delivery route prediction problems. These methods typically use deep neural networks to learn courier route patterns from large amounts of historical data in a supervised manner. oSquare transforms route prediction in a food delivery service into a next-location prediction problem, outputting each location in the route step-by-step. ZDNet proposes a route prediction module based on a recurrent neural network and an attentional mechanism that simultaneously predicts the time to arrive at each location. DeepRoute predicts routes using a Transformer-based encoder and a pointer network-based decoder.Graph2Route proposes a dynamic spatio-temporal graph-based neural network to implement route prediction.

Despite the results achieved by these deep learning-based methods, all of them have some limitations: the training and testing objectives are not aligned, which will limit the performance of these methods. All of these methods use cross-entropy as a loss function during model training, but use other evaluation metrics such as position squared deviation and Kendall rank correlation coefficient during testing. Although the route prediction results in both cases achieved the same results on the training objectives, they have large differences in the test metrics of position squared deviation. Inconsistency between the training and testing objectives will limit the performance of a trained model, so we will seek an effective solution that allows the model to differentiate between the two cases of inconsistency in the testing objectives mentioned above during training.

3.1. Methodological Model

An intuitive solution is to transform the test targets into loss functions for updating the model parameters. However, this approach is infeasible because the test targets in this task, such as the position squared deviation, and the Kendall rank correlation coefficient, are non-microscopic. These test targets compute the similarity between the real and predicted routes, and the predicted routes are generated step by step by taking the maximum of the probability distribution of the model outputs. Since these test targets are non-differentiable, there is a need to find a way to use the test targets to guide the model training to achieve better results on the test metrics. In recent years, reinforcement learning has been widely used to optimize non-differentiable test objectives in a variety of tasks, such as machine translation, text summarisation, image description, etc., achieving better results compared to supervised deep learning methods on these tasks.

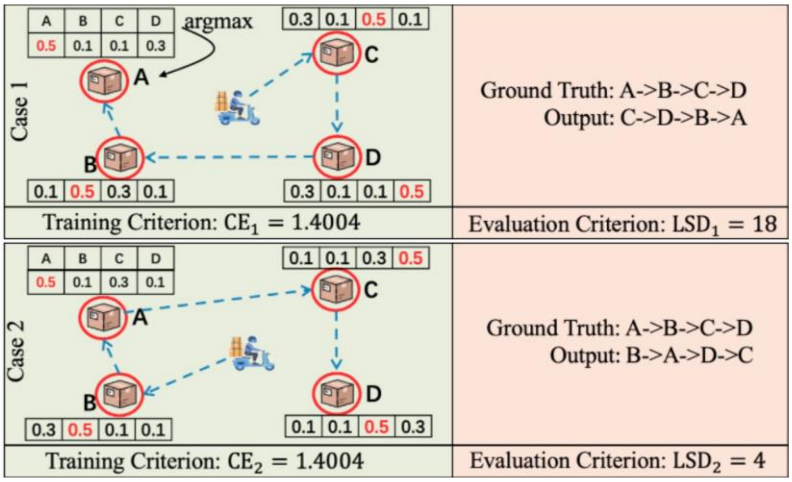

Figure 1. Illustration of the mismatch between the training and test objectives. The vector near each location is the transition probability corresponding to A, B, C, and D.

This paper is the first to model the route prediction problem of dispatching from the perspective of reinforcement learning and to construct the training framework DRL4Route using a policy-based reinforcement learning approach, which is based on the rewards computed from non-differentiable test objectives optimizing the deep neural network through a policy gradient approach to solving the problem of inconsistency between the training and the test objectives. Based on this framework, we designed the DRL4Route-GAE model for route prediction in logistics collection services. Based on the strategy gradient algorithm,1 DRL4Route-GAE reduces the variance in gradient estimation based on the actor-critic framework, which produces some bias in gradient estimation due to the inability of the critic model and the actor model to accurately estimate the value function. To balance the bias and variance of the actor-critic framework at gradient estimation, the generalized dominance estimation method is used to estimate the dominance value when updating the loss function. Overall, the contributions of this paper are as follows:

1. the first time the task of collection and delivery route prediction is solved from a reinforcement learning perspective and proposes a reinforcement learning-based framework, DRL4Route, which combines the ability of reinforcement learning in optimizing an undifferentiable objective function and the ability of deep neural networks to learn historical behavioral patterns, compared to previous supervised learning approaches.

2. propose the DRL4Route-GAE model for route prediction in logistics scenarios, which utilizes an actor-critic framework to compute rewards at each decoding step designed by the test objective to guide model training, and computes an approximation of the dominance using a generalized dominance estimation to balance the bias and variance during gradient estimation.

3. Extensive offline experiments on real datasets as well as online deployments validate the effectiveness of the method proposed in this paper. Compared to the optimal baseline method, DRL4Route-GAE improves the location bias squared metrics by 0.9%-2.7% and the top three location prediction accuracy metrics by 2.4%-3.2%.

3.2. DRL4Route

The DRL4Route (Deep Reinforcement Learning for Route Optimization) model is a route optimization algorithm based on deep reinforcement learning, which is specifically used to solve complex logistics route planning problems. The model can autonomously learn and optimize transport routes by using reinforcement learning strategies, thus effectively reducing transport time and cost. Its advantages in logistics forecasting are mainly reflected in the following aspects: firstly, the DRL4Route model can dynamically adapt to changing logistics demand and traffic conditions and provide real-time optimization solutions; secondly, it can efficiently process large-scale data, and can quickly find the optimal paths in a complex network; lastly, the DRL4Route model, through continuous learning and improvement, can continuously enhance the precision and efficiency of route planning, thus significantly improving the overall performance and response speed of the logistics system.

This framework updates the parameters of the intelligence based on the rewards computed from the test objectives using a policy gradient approach. This allows us to optimize the non-differentiable objective function for more accurate route prediction. If the intelligent body selects an action that is favorable for the test metrics to improve, the reward value will be higher, so this action will be encouraged and the parameters of the intelligent body will be updated toward the execution of this action. If an action unfavorable to test metrics improvement is performed, the reward value will be lower and the parameters of the intelligent body will be updated in the direction of avoiding the execution of such an action.

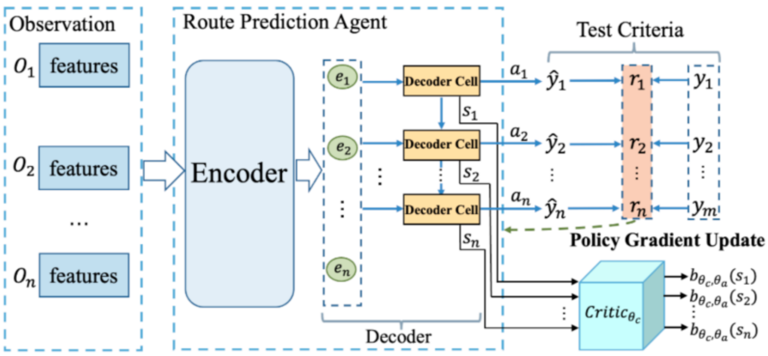

Figure 2. DRL4Route Framework.

In this paper, based on the DRL4Route framework, a model named DRL4Route-GAE is proposed for parcel collection services in logistics scenarios to illustrate the effectiveness of the proposed framework.DRL4Route-GAE generates the spatio-temporal representation of the unfinished task using a transformer-based encoder and models the decision-making process of the courier by using an attention mechanism and recurrent neural network-based decoder to model the courier's decision-making process. The model training is guided by the strategy gradient so we can optimize the non-differentiable test objective to solve the problem of inconsistency between the training and test objectives, furthermore, we use a generalized dominance estimation method to compute an approximation of the dominance to balance the bias and variance during gradient estimation, so we can get better strategies as well as better results.

3.3. Experimental Data Sets and Methods

We conduct offline experiments on the logistics parcel-acquisition dataset provided by Cainiao, and the sample ratio of the training set, validation set, and test set is about 6:2:2, and the data statistical information is shown in Table 1.

Type	Time Range	City	ANUT	#Workers	#Samples
Logistics-I1Z	07/10/2021-10/10/2021	Ilangzhou		1,117	373,072
Logistics-SI1	03/29/2021-05/27/2021	Shanghai		2,344	208,202

Baseline methods

This paper implements a variety of baseline methods, as well as some state-of-the-art deep models in different scenarios (food distribution and last mile logistics) for comparison:

Time Greedy: Generate paths by ranking all locations to be visited based on the time remaining until the task timeout.

Distance Greedy: Selects the closest location to the courier to visit each time and completes the path generation step by step.

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OR-Tools: a heuristic algorithm to find the shortest path.

OSquare: an XGBoost-based method that generates the route one node at a time.

FDNET: A path and time prediction model for takeaway scenarios using LSTM and attention mechanisms.

DeepRoute: A deep learning route prediction model based on a Transformer encoder and attention decoder.

DeepRoute+: Based on DeepRoute, a courier decision preference modeling module is added to the coding.

Graph 2Route: For the first time, a graph is used to model the locations to be visited by couriers, and a GCN-based encoder and attention mechanism are used to complete the path prediction.

3.4. Experimental Results

As can be seen from the results on the two datasets in Table 2, the distance-based greedy or time-greedy methods, as well as OR-Tools, only consider distance or time alone, and their results are only optimal solutions under a particular strategy, ignoring a large number of spatio-temporal constraints. The tree-based model OSquare cannot model spatiotemporal correlations, and in addition, its goal is to maximize the output probability of the next position rather than the entire route. Sequence-based models DeepRoute and [16] FDNET have difficulty in modeling neighborhood relationships between locations, and thus they may provide unreasonable outputs.Graph2Route attempts to address this problem by introducing a graph-based encoder, while Graph2Route captures decision context information.

Table 2. Experimental result.

Method	**Logistics-HZ n E(0.25]**	**Logistics-HZ n ∈(0.11]**	**Logistics-SH n E(0.25]**	**Logistics-SH n ∈(0.11]**
	HR@I	ACC@3	KRC	LMD
Time-Greedy	33.15	20.32	41.92	1.7
Distance-Greedy	33.13	51.82	136	5.73
OR-Tools	53.93	1.23	4.68	1.46
OSquare	54	33.1	58.5	1.16
FDNET	52.76	33.22	55.47	1.18
DeepRoute	54.76	34.64	58.61	1.1
DeepRoute+	55.42	35.63	59.32	1.08
Graph2Route	56.45	36.12	60.63	1.05
DRLAROute-REINFORCE	55.88	29.02	59.97	1.38
DRL4Route-AC	56.36	36.16	60.86	1.05
DRL4Route-GAE	57.72	37.23	61.47	1.03
Improvement	2.20%	3.10%	1.40%	1.90%

Based on DeepRoute, DRL4Route-REINFORCE achieves better results, especially on the metric of the squared deviation of position, DRL4Route-REINFORCE directly optimizes the evaluation metrics and therefore solves the problem of inconsistency between training and testing metrics. Compared to DRL4Route-REINFORCE, DRL4Route-AC achieves better results because DRL4Route-AC updates the model parameters using the dominance values computed by the rewards at each time step, alleviating the problem of error accumulation. By using the generalized dominance

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estimation method to balance the bias and variance during gradient estimation, DRL4Route-GAE achieves better results than DRL4Route-AC.

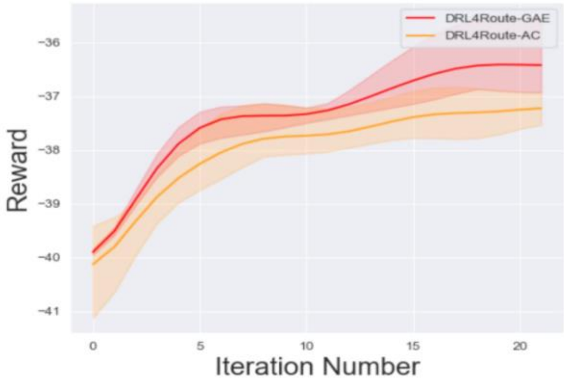

Figure 3. Different performance curves for algorithms [17] DRL4Route-GAE and DRL4Route-AC.

In Figure 3, the changes of cumulative expected rewards of DRL4Route-AC and DRL4Route-GAE are compared during the training process, and the reward values of both methods increase with the increase of the number of training rounds, which demonstrates the effectiveness of the framework proposed in this paper, and finally, DRL4Route-GAE is better than DRL4Route-AC and its reward value is also higher, which illustrates the effectiveness of the generalized dominance estimation method in balancing the bias and variance in the gradient estimation and ultimately results in a superior strategy.

Since the test objectives are non-differentiable, deep models applied to the task of range and delivery path prediction are unable to introduce the test criteria into the training process under the supervised training paradigm, resulting in a mismatch between the training and test objectives, which severely limits their performance in real systems. To address the above problems, we apply reinforcement learning methods to the collection and delivery path prediction tasks for the first time and propose a new framework called DRL4Route. It combines the current behavioral pattern learning capabilities of deep neural networks with reinforcement learning's ability to optimize non-micro-objectives. Furthermore, DRL4Route can be used as a plug-and-play component to improve the performance of existing deep models. Based on this framework, we implement a reinforcement learning-based model, DRL4Route-GAE, for solving the route prediction problem in logistics, which is based on an actor-critic architecture and uses a generalized dominance estimation method that balances the bias and variance of the strategy gradient estimation. We experimentally demonstrate that DRL4Route achieves significant improvements over the most competitive baseline models on real datasets.

4. Conclusion

This paper reveals the importance of intelligent logistics algorithms in modern logistics systems by reviewing the development history of traditional logistics technologies and exploring the key roles of the Internet of Things (IoT), big data analytics, artificial intelligence (AI), and automation technologies in logistics technology innovation. In particular, the proposal and application of DRL4Route, a deep reinforcement learning-based path optimization framework, demonstrates its significant advantages in improving logistics path optimization, intelligent scheduling, and prediction accuracy through extensive offline experiments and online deployments on real datasets. The DRL4Route-GAE model significantly outperforms the positional bias squared metrics and the top three positional prediction accuracy metrics of the existing optimal benchmark methods. Overall, these research results not only improve the efficiency and accuracy of logistics transport but also provide solid technical support and direction guidance for the intelligent development of the logistics industry.

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Major trends in future logistics technology innovation include the evolution of intelligent logistics systems, the widespread application of emerging technologies, and the rise of green logistics technologies. Intelligent logistics systems will integrate automation, artificial intelligence, and big data analysis more deeply, and use deep learning algorithms to enhance data processing and decision-making capabilities. The adoption of edge computing will accelerate real-time response, while human-machine collaboration technologies will enhance cooperation between humans and intelligent systems to jointly improve logistics efficiency. Emerging technologies such as 5G, IoT, and edge computing will be applied on a large scale in the logistics sector. the high-speed transmission of 5G technology will enhance real-time monitoring and remote operations, the expansion of IoT will connect more devices and sensors, and edge computing will ensure that data is processed quickly at the edge of the logistics network. At the same time, the logistics industry will be committed to sustainability. Electric and self-driving vehicles will reduce carbon emissions, the circular economy concept will promote the reuse of packaging materials, and smart energy management will optimize energy use and reduce resource waste. In the future, intelligent green port management systems and circular economy logistics networks will become a reality, driving smarter and more efficient logistics systems and promoting the industry toward more sustainable and environmentally friendly development.

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