Preliminary Investigation of Crowd-shipping with Real-world Data: A Case Study of Atlanta, GA

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Introduction

Crowd-shipping (CS) is a platform that connects senders' delivery requests with occasional couriers who are willing to deliver goods using their available vehicle capacities or professional couriers, such as Deliv, Postmates, PiggyBee etc..

Some researchers have studied the characteristics of CS senders and couriers by survey data. People who earn less money, use multiple social media outlets want to be couriers, and they prefer requests that are not for long distance and with flexible time windows (Le et al., 2019; Miller et al., 2017; Marcucci et al., 2017; Paloheimo et al., 2016). Punel and Stathopoulos (2017), Frehe et al. (2017), and Punel et al. (2018) find that youth, full-time employed people, and people with a strong sense of environmental concerns prefer CS service. Currently, there is very limited understanding of the two-sided CS market (senders and couriers).

Therefore, this paper aims to analyze the real-world CS data, which was collected between April 2015 and August 2018 from a CS platform. Using the Atlanta city, GA as a case study, the investigation focuses on these aspects: (1) the CS pricing model; (2) spatial and temporal distribution of the CS delivery requests; and (3) characteristics of senders' requests and couriers' preferences.

The results conclude the advantage of the CS pricing model compared to conventional delivery (CD) service, the obvious imbalanced spatial and temporal distribution of delivery requests by zipcode, the discrepancy between senders' requests and couriers' preferences, and the good predictive performance of two DL methods.

Methodology

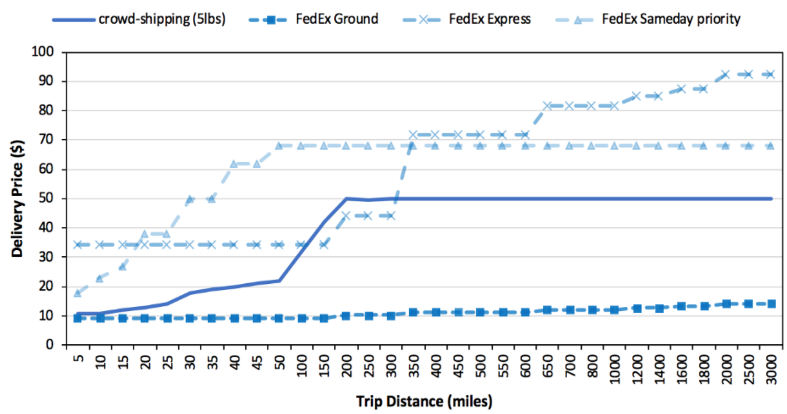
Long short-term memory neural network (LSTM) considers the dependent variable in one timestamp not only depends on explanatory variables in current timestamp but also in previous timestamps (Williams and Zipser, 1989; Sutskever et al., 2009). It enables storage of long-term information with a series of memory cells in hidden layers (Hochreiter and Schmidhu, 1997). The standard structure of LSTM includes one input layer, one or more hidden layers, and one output layer. The forget gate f_t, input gate i_t, and output gate o_t on hidden layers are used to control and change cell state C_t. When input data, f_t determines which information should be removed from the previous cell state C_{t-1}, i_t decides what information should be added to the cell state C_t, and o_t decides which information from the current cell state C_t is used to create the output h_t.

Bidirectional long short-term memory neural network (BDLSTM) is the extension of LSTM by adding hidden layers in the backward direction (Zhu et al., 2018). The final output is the combination of outputs from forward and backward layers (Li et al., 2017).

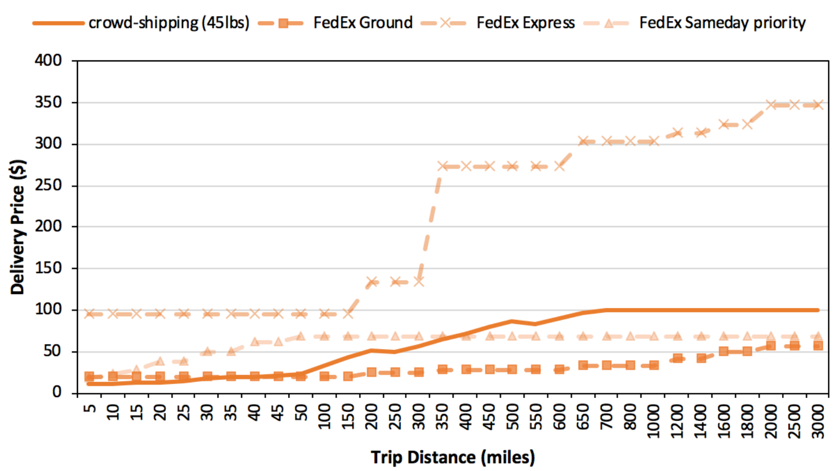
Results

CS Pricing model

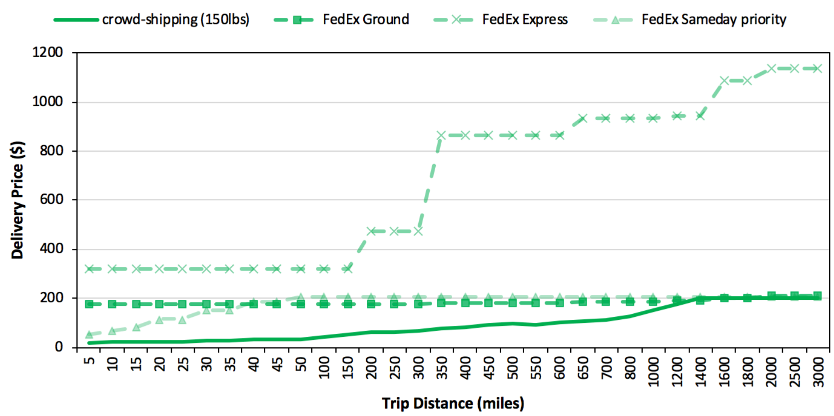
The basic CS pricing model need to consider package size, while the conventional delivery (CD) pricing model, taking the FedEx as the example, considers package weight. Therefore, we firstly convert package size to dimensional weight as the chargeable package weight, then compare the prices of the CS and the FedEx for small (with a dimensional weight of 5 lbs), medium (45 lbs) and large (150 lbs) packages respectively. Figure 1 indicates the obvious advantage of the CS pricing model. Especially when packages are required to be delivered within short time periods.



(a) Delivery price of a small size package (5 lbs)



(b) Delivery price of a medium size package (45 lbs)

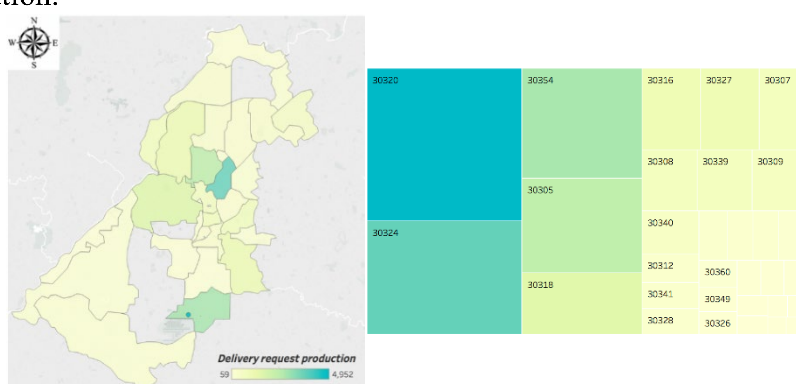


(c) Delivery price of a large size package (150 lbs)

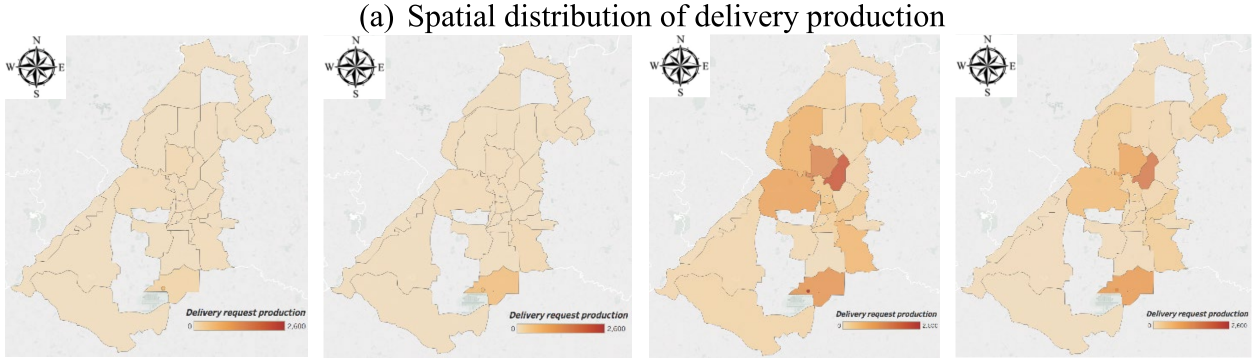
Figure 1 Comparison of pricing models between CS and CD service

Spatial and temporal delivery patterns of CS

We group the CS delivery requests into four time periods of a day, 0:00-6:00am, 6:00am-12:00pm, 12:00-18:00pm, and 18:00pm-0:00am, to analyze temporal patterns. Taking the CS delivery production as the example, Figure 2(a) finds the significant variations in spatial distribution, and Figure 2(b)-(e) show the distribution over four time periods is also different. The same way to analyze CS delivery attraction, and we also find the obvious imbalanced spatial and temporal distribution.



(a) Spatial distribution of delivery production

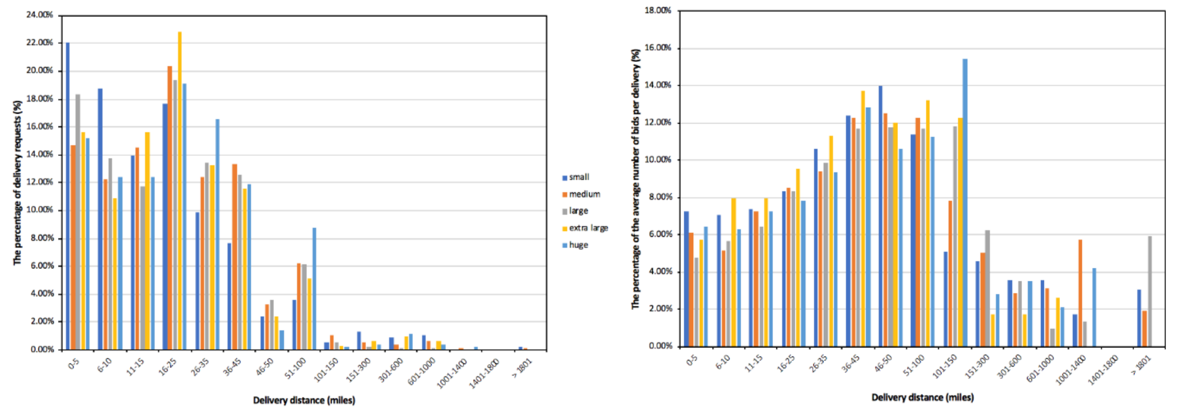


(b) 0:00-6:00am (c) 6:00am-12:00pm (d) 12:00-18:00pm (e) 18:00pm-0:00am

Figure 2 Spatial and temporal distribution of delivery production by zipcode

Discrepancy between CS senders' and couriers' preferences

From delivery distance, package size, delivery price, declared value, and time window aspects, this paper analyzes the characteristics of CS senders' requests and couriers' bidding preferences. For the delivery distance, Figure 3 finds senders prefer to send requests within 25 miles, while couriers prefer to bid requests within 26-100 miles. For package size, delivery price, declared value, and time window, applying the same way to analyze and shows senders prefer to send package no more than large size, with cheaper price, smaller declared value, and strict time windows, while couriers prefer to bid packages no less than large size, with higher price, bigger declared value, and flexible time windows.



(a) CS delivery requests (b) the number of CS bids per delivery

Figure 3 Distribution of CS demand and supply by **delivery distance**

Prediction of delivery productions with deep learning methods

Due to the imbalanced distribution of delivery production over 31 zipcode, the delivery data in the top 5 zipcode are used to build LSTM and BDLSTM models to predict short-term delivery production. The explanatory variables include delivery production, weather condition, and four time periods. In order to validate the DL methods, some traditional parametric and ML models are also trained by Python. The results demonstrate that LSTM and BDLSTM outperform other methods in terms of Root Mean Squared Error (RMSE).

Conclusion

This study firstly conducted a comprehensive preliminary investigation based on one real-world CS data, then predicted delivery production and destination choice by DL and ML methods.

Based on descriptive analysis, we find the advantage of the CS pricing model, the obvious imbalanced spatial and temporal distribution of delivery requests, and the discrepancy between senders' and couriers' preferences. For the prediction of delivery production and destination choice, the developed LSTM, and BDLSTM obtain good predictive performance. In particular, BDLSTM predicts a little better than LSTM.

The contributions of this paper are multitude. First, the comparison of the CS pricing model and the FedEx pricing model is beneficial to understand the novelty service. Second, the discrepancy between senders' requests and couriers' bidding preferences is unique to CS as compared to ridesourcing. Third, it is among the first to apply DL methods to CS delivery production forecasting that is based on one real-world CS data.

However, there are some limitations. First, this study does not consider the social-economic characteristics of each zipcode, senders, and couriers. Second, the proposed DL methods are unable to explain how important factors affect delivery demand. Finally, we still have limited understanding of the CS. In particular, why is CS not as popular as the ridesourcing? How to match senders' requests with couriers' preferences?

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References

1. Frehe, V., Meehmann, J., Teuteberg, F., 2017. Understanding and assessing crowd logistics business models-using everyday people for last mile delivery. The Journal of Business & Industrial Marketing, 32(1), 75-97.
2. Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9(8), 1735-1780.
3. Le, T.V., Stathopoulos, A., Woensel, T.V., Ukkusuri, S.V., 2019. Supply, demand, operations, and management of crowd-shipping services: A review and empirical evidence. Transportation Research Part C: Emerging Technologies 103, 83-103.
4. Li, S.M., Chen, J.J., Liu, B., 2017. Protein remote homology detection based on bidirectional long short-term memory.
5. Marcucci, E., Pira, M.L., Carrocci, C.S., Gatta, V., Pieralice, E., 2017. Connected shared mobility for passengers and freight: Investigating the potential of crowdshipping in urban areas. In: Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017 5th IEEE International Conference on. IEEE, 839-843.
6. Miller, J., Nie, Y., Stathopoulos, A., 2017. Crowdsourced urban package delivery: Modeling traveler willingness to work as crowdshippers. Transportation Research Record: Journal of the Transportation Research Board 2610, 67-75.
7. Paloheimo, H., Lettenmeier, M., Waris, H., 2016. Transport reduction by crowdsourced deliveries – A library case in Finalnd. J. Clean. Prod. 132, 240–251.
8. Punel, A., Ermagun, A., Stathopoulos, A., 2018. Studying determinants of crowd-shipping use. Travel Behaviour and Society 12, 30-40.
9. Punel, A., Stathopoulos, A., 2017. Modeling the acceptability of crowdsourced goods deliveries: Role of context and experience effects. Transportation Research Part E: Logistics and Transportation Review 105, 18-38.
10. Sutskever, I., Hinton, G.E., Taylor, G.W., 2009. The recurrent temporal restricted boltzmann machine. In: Advances in Neural Information Processing Systems, 1601-1608.
11. Williams, R.J., Zipser, D., 1989. A learning algorithm for continually running fully recurrent neural networks. Neural Comput. 1, 270-280.
12. Zhu, J.S., Sun, K., Jia, S., Lin, W.D., Hou, X.X., Liu, B.Z., Qiu, G.P., 2018. Bidirectional long short-term memory neural network for vehicle behavior recognition. Remote Sensing10(6), 887.