# Potential Big Data Future Challenges for the GoodTurn System

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***Abstract*—GoodTurn is an application designed and implemented by the University of Detroit Mercy through a grant from Ford Motor Company. It is a goods-moving system. In a manner similar to Uber, the application is aimed at facilitating and managing Ford employees' donation of their time and vehicles to assist the community by moving their goods and resources. The stakeholders—drivers, donors, and nonprofit/nongovernment organizations (NPO/NGO)— will use their iPhones and Android-based phones to connect to the application free of any charge. Increasing amounts of data are currently being generated. It is anticipated that the data will exceed one terabyte in the next few years. To address the benefits of the availability of future big data, this paper will present potential future challenges of the resulting big data's analytics. In particular, these challenges will address the decision-making needs of Ford, NPOs/NGOs, drivers, and donors. The paper will not address the implementation of any actual big data analytics using tools as the data is not yet completely developed. However, once the anticipated big data is generated, appropriate tools will be employed to obtain the needed knowledge and uncover the value of the stored data.**

***Keywords—GoodTurn System; Big Data Analytics; Big Data Lifecycle; Prediction; Classification; Clustering***

## I. INTRODUCTION

GoodTurn is a system developed by the University of Detroit Mercy with a grant from Ford Motor Company to facilitate the work of nonprofit/nongovernment organizations, NPOs/NGOs, when dealing with donors. Ford's employees volunteer their vehicles and time to move goods and resources donated by people to the NPOs/NGOs designated locations. GoodTurn currently runs on iOS-based devices, with Android and web-based versions being developed. It is anticipated that this application will generate big data in the near future.

Currently, we are experiencing an explosion in the rate of the quantity of big data being generated due to the ever-increasing amount of data resulting from Web applications, networks, log files, vehicle performance, social media tweets, mobile applications, transactional applications, and sensing devices. These big data include massive potential hidden knowledge that can add business value to a variety of fields including healthcare, biological systems, transportation, online advertising, crash reporting, performance monitoring, energy management, student registration and financial services [1]-[3]. Innovations with big data vow to transform the way we live, work, and think by empowering process optimization, facilitating insight discovery and improving decision making [4]. With the evolution and improvement of web and other technologies, the enormous amount of data of different types is briskly generated and the amount of knowledge multiplies drastically [5][6]. Users are saturated with data in this big data time, however, identifying valuable data to obtain worthwhile information and knowledge has never been an easy task. Uncovering valuable information from the titanic amount of data is becoming more important, and many countries and enterprises are devoting time and money to acquirement and analysis of data [7].

Big data is generally defined by the three Vs; Volume, Velocity, Variety, and it has been very vital and constructive in achieving treasurable values with regards to supporting decision making, illuminating new insights, and process optimization [8]. The bulk of data created is constantly growing and taking the form of a variety of structures, and can be in motion and at rest. For example, Google receives over one billion queries per day, Twitter gets more than two hundred and fifty million tweets on a daily basis [9], Facebook goes through more than eight hundred million updates per day, and YouTube causes more than four billion views per day. The data generated is estimated in the order of zeta bytes at the present time, and it is intensifying at a rate around 40% per year [10].

Big data analytics involves applying advanced analytic techniques to exceedingly large and diverse datasets with the possibility of including structured, semi-structured, and unstructured data to explore new capabilities and insights [11]. If big data analytics techniques are deployed in a timely manner, the outcome can produce actionable insights that add significant value to organizations and help them improve the decision-making process, and create various opportunities for business improvements and success [12]-[13].

E. Žunić, A. Djedović, and D. Đonko [14] indicated that assorted types of mobile communication devices are more frequently used to access applications. They added that with mobile devices, anyone can clearly use or even develop a mobile application adding to the further explosion of applications and data. Mobile communication networks grant an immense range of communication services producing a substantial amount of network data [15]. The current innovations of wireless technologies in various forms and the constantly increasing mobile applications have turned mobile cellular networks into both generators and carriers of massive data [16].

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The GoodTurn system was developed by the University of Detroit Mercy with a grant from Ford Motor Company. The goal of the application is to facilitate the moving of goods and resources donated by individuals to various NPOs/NGOs. To this extent, Ford employees (drivers) volunteer their vehicles and time to move these goods from donors' locations to the NPOs/NGO's locations. The GoodTurn application runs on iPhones and will soon run on Android-based phones. As stated above, mobile applications generate massive data. It is anticipated that GoodTurn will produce a terabyte within the next few years. This paper discusses a number of possible big data analytics applications when the big data matures. The outcomes of these applications will furnish actionable insight to Ford Motor Company, NPOs/NGOs, donors, and drivers. The rest of the paper is organized as follows: Section II will provide a brief description of the GoodTurn system. Section III will introduce the evolution of the GoodTurn big data. The GoodTurn big data lifecycle is presented in Section IV. Section V highlights the potential analytics of the future big data. Finally, the paper is concluded in Section VI.

## II. GOODTURN SYSTEM DESCRIPTION

To get the flavor of the GoodTurn system, sample requirements and an overview of the system architecture with sample interface will be presented. Details of the GoodTurn software design are introduced in [17]. Security of the GoodTurn system is discussed in [18].

### A. *Functional requirements*

The GoodTurn system has been developed using the client-server methodology. The clients will be accessing the system using iPhones, and Android-based phones. The GoodTurn system's functional requirements were gathered from Ford employees, non-profit organizations (NPOs), non-government organizations (NGOs), and the public. Samples of these requirements are shown below. Here, "requesters" represent NPOs or NGOs.

- The login screen must contain an option to save the user's email.
- The system must allow the requestor to reject a specific driver in the future.
- The system must allow the driver to reject a specific requestor/organization in the future.
- The system must allow the requester to verify a job was completed.
- The system should allow the user to register if they do not already have an account.
- The system must allow rating of users that were involved in a job.
- The system must allow users that were involved in a job to provide feedback.
- The system must provide a list of available jobs.
- The system should allow the driver to accept a job.
- The system must allow drivers to cancel accepted jobs.
- The system must allow the requester to start a new job.

### B. *Nonfunctional requirements*

The constraints on the GoodTurn's functional requirements include performance, usability, security, privacy, reliability, and maintainability features. A small sample of these nonfunctional requirements will be presented below.

- The system should allow drivers and requesters to sign in within 5 seconds.
- Displaying blacklisted drivers for a specific requester should take no more than 5 seconds.
- Drivers and requesters should be able to use the system without any training.
- The system should provide messages to guide the users when invalid information is entered.
- Drivers, requesters, and system administrators should be authenticated
- Messages exchanged between all parties (drivers, requesters, system administrators) should be confidential.
- The system should not disclose requester information to non-drivers.
- The system should not disclose a driver information to non-requesters.
- The system must detect, isolate, and report faults.
- Backup copies must be stored at a different location specified by the NPO/NGO.
- Errors should be easily corrected using effective documentation.
- Additional features should be added without considerable changes to the design.

### C. *System architecture*

An architecture embodies the high-level structures of a software system. By examining the architecture, one can conclude how multiple software components collaborate to accomplish their tasks. GoodTurn follows the three-tiered client-server architectural style. The GoodTurn system architecture is functionally decomposed into various functional components. To illustrate that, Figure 1 is used to demonstrate the top-level and first-level decompositions. The component, GoodTurn Startup, is further decomposed into second and third levels in Figure 2 below.

### D. *User Interface*

To design a user interface for GoodTurn system, the humans that need to interact with the system need to be identified. These include drivers, NPOs/NGOs, donors, and

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system administrators. Later, settings for each way the user can communicate with the system need to be established. Samples of the User Interface are provided in Figures 3 and 4 below.

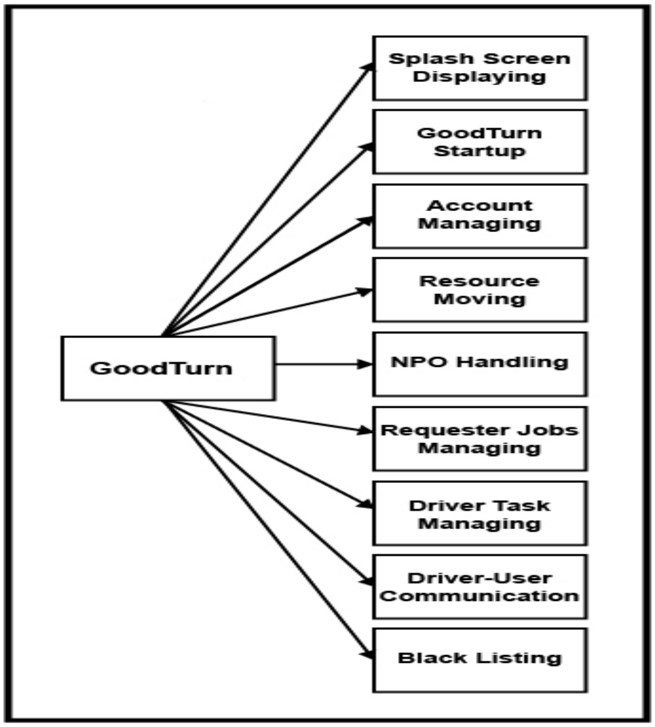


Figure 1. Top-level decomposition

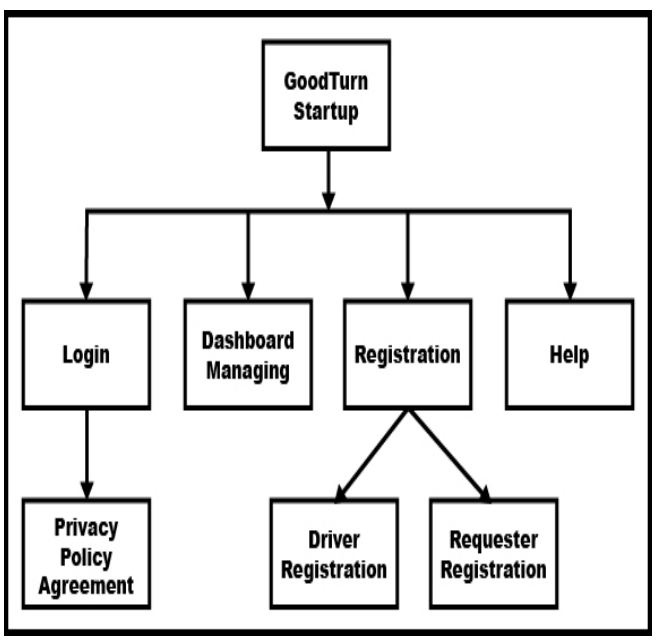


Figure 2. Second/Third levels decomposition


Figure 3. Available jobs for drivers

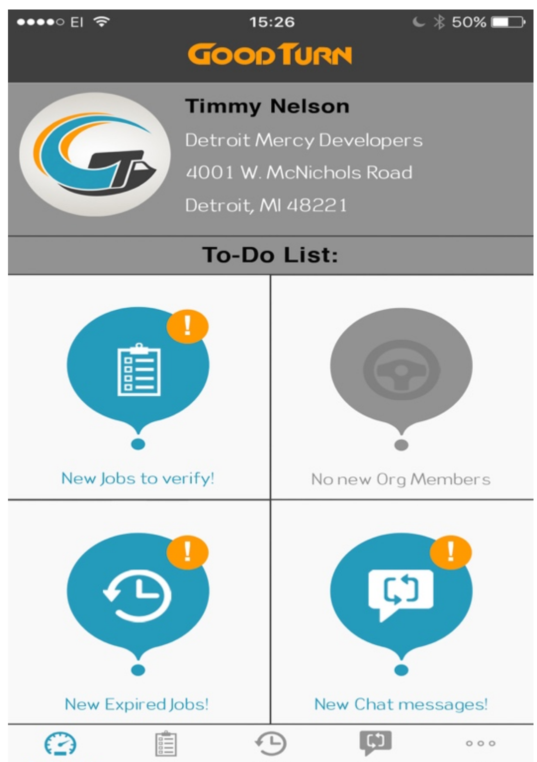


Figure 4. Requester's new job

## III. EVOLUTION OF GOODTURN BIG DATA

The GoodTurn system data currently has 404 bytes for each of the stakeholders; NPO, drivers, and donors. In addition, there is a total of 76 bytes for the metadata. This will give a total of 480 bytes per a stakeholder. This represent structured data only. The above data size does not include the huge unstructured data resulting from various feedbacks fields. Details of the data are depicted in Tables I and II below.

There are 75,437 nonprofit organizations (NPOs) in Michigan State [1]. Ford Motor Company's workforce is over 201,000 employees worldwide [2][3]. Michigan has total of 9,928,300 residents [4]. They contribute the equivalent of almost $5 billion to charity each year [5]. This implies that many of those residents donate at least once a year.

The exact figures of NPOs, donors and drivers will be determined when GoodTurn is implemented. These numbers of donors, drivers, and NPOs will continue to grow. As an example, the total number of NPOs in 2013 was 42,886 [6]. Comparing this to 75,437 nonprofit organizations in 2017, it can be concluded it is almost doubled. This implies there will be even more data in the future. Based on these figures, it is anticipated that the GoodTurn application's big data will develop in the near future ahead

TABLE I. INDIVIDUAL STAKEHOLDER DATA TOTALS

| Category | Total Bytes |
|---|---|
| Account | 081 |
| Job | 260 |
| Chat | 005 |
| Dashboard | 028 |
| Misc. | 030 |
| Total | 404 |

TABLE II. METADATA TOTALS

| Category | Total Bytes |
|---|---|
| Account Metadata | 28 |
| Job Metadata | 28 |
| Chat Metadata | 08 |
| Dashboard Metadata | 04 |
| Misc. Metadata | 08 |
| Total | 76 |

## IV. GOODTURN BIG DATA LIFE CYCLE

The life cycle of GoodTurn big data analytics starts with the generation of big data. Data will continue to accumulate and reach more than a terabyte within few years. A decision should be made whether to store this big data on the cloud or on the GoodTurn server. Both approaches involve security and cost issues. The data needed for big data analytics will be selected and filtered. The filtering will encompass removing the data items that are not desirable for the analytics, and handling missing data values. Once filtering has been taken care of, the needed techniques, tools, and algorithms will be applied to achieve the analytics. As discussed in Section V below, the potential analytics will concentrate on predictions, classification, and clustering. The outcomes of these analytics would be actionable knowledge and insights beneficial to various stakeholders. Once the insights are available, the stakeholders; Ford, NPOs/NGOs, drivers, and donors, will be able to use these insights to inform decisions. The next cycle will start at big data generation with more data generated. This cycle is depicted in Figure 5 below.

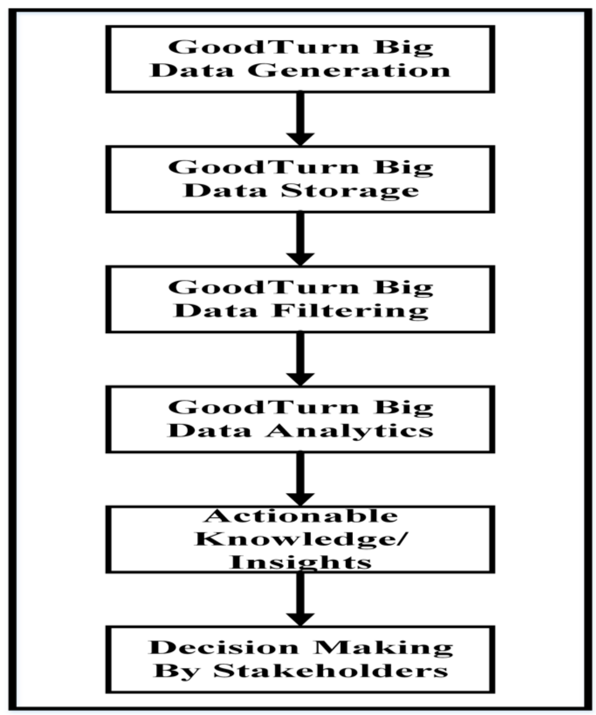


Figure 5. GoodTurn big data lifecycle

## V. POTENTIAL ANALYTICS

Potential future analytics when the big data matures will be discussed. These proposed potential analytics will be linked to the GoodTurn's stakeholders. In other words, each stakeholder can only own the analytics with which they are concerned.

### *A. Ford Motor Company*

The quality of vehicles and quantity of sales are important factors in automotive industry. The analytics below should address these concerns. Ford Motor Company also values and promotes philanthropic activities for its employees.

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Note that analytics in bullets; 2,3, 4, and 5 will only be possible if the GoodTurn system allows comments regarding the selected type/model of vehicles in the Feedback field. Currently, this is not the case, but it is anticipated that will be the case in the future.

- *Predicting the demand for specific Ford vehicles*: NPOs/NGOs select the type of vehicle for moving the donor's goods/resources. Within the NPOs/NGOs, individuals decide the size of vehicle. Selecting the size of the vehicle will imply selecting the type/model of the vehicle because these data are already available for those individuals. If some vehicles are frequently selected, then those vehicles reflect the taste of users and could indicate these are preferred or on demand. Therefore, the *characteristics* of those *individuals* will reflect the type of people who would possibly buy such vehicles. Ford can continue to promote these vehicles and improve their future models. For vehicles that are infrequently requested, Ford will study the reasons behind that and improve these vehicles. If non-Ford employees are allowed to be drivers in the future, *competitive* vehicles will be involved. If some non-Ford vehicles are frequently used, then the *characteristics* of those individuals will guide Ford to investigate all the *design* aspects of the frequently competing demanded vehicles and make decisions on Ford competing vehicles.
- *Determining the characteristics of individuals who will complain about certain vehicles*: Complaining about a vehicle should be interpreted as complaining about the type and model of the vehicle. NPOs/NGOs and donors provide feedback after the job is completed. They can also provide feedback if they have to cancel the job while in transit. The feedback containing complains about the vehicles can be analyzed to find out from this sample the type of individuals that might be complaining about certain type/model of vehicles in the future. The resulting analytics could lead to improving those vehicles. In other words, those complains would be interpreted as *buyers'* needs. Therefore, people with similar *characteristics* can be targeted using the improved vehicles. If the *complains* are about competitor's vehicles, Ford can approach buyers by promoting the features/*characteristics* their vehicles have as compared to others.
- *Predicting the characteristics and features of vehicles that individuals might complain about*: Based on various complains about the vehicles used in moving goods, various features and specifications of those vehicles will be analyzed to conclude the features that might have caused these *complains*. Further testing and investigation will be carried out to isolate the focal *features*. Having done that, those features will either be avoided or improved in other models that share the same characteristics in the future. If the *complains* are about *competitor's* vehicles, Ford will check if the predicted features causing the complains exist in their vehicles and improve them.
- *Predicting whether a new driver (volunteer) will undergo complains*: By *analyzing* the feedback about drivers, Ford can use the *characteristics* of the drivers undergoing complains and classify if a new volunteer (driver) might encounter complains. This outcome can be used to effectively screen future drivers.
- *Isolating the characteristics and features of vehicles that will experience frequent problems*: Vehicles in transit can experience problems. These problems will be documented in the feedback. By analyzing those vehicles' features, Ford can determine the features causing the problems and issue the necessary recalls to fix these problems. They can further decide to illuminate some features from future vehicles if fixing/replacing them becomes costly or displeasing.
- *Identify clusters of potential buyers for certain vehicles*: Taking the possible analytics above, and provided the NPOs/NGOs and donors are from specific geographic location, Ford can determine the characteristics of such a geographic location to identify other geographic locations that have similar characteristics to market on-demand vehicles in those areas.

### B. NPO/NGO

Nonprofit and nongovernment organizations are interested in getting good number of donors, certain types of goods, concentrating on geographical areas that have frequent donors or many donors, ensuring the selected drivers are reliable.

- *Identifying geographic locations of possible frequent donors*: By analyzing the geographic locations of current donors, an NPO/NGO can select other geographic locations with similar characteristics and properties that could possibly provide frequent donors.
- *Detecting geographic locations of maximum number of donors*: Using the current geographic locations containing the maximum number of donors (not necessarily frequent donors), an NPO/NGO can use the qualities and features of these locations to find out similar geographic locations to target them for possible high volume of donors.
- *Anticipation of a needed type of goods*: This potential analytic can be achieved in two ways. First, a similar analysis to the geographic locations above could be carried out to determine the potential geographic locations that may donate the needed goods and resources based on the traits of current locations providing the needed type of goods. Second, an NPO/NGO can use the characteristics of individuals who donate such needed type of goods to focus on individuals with the same characteristics.

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- *Association of a needed type of goods*: NPOs/GPOs can look for features of individuals who donate goods that complement each other (table and chairs for example), and then use these features to aim at possible donors who may donate goods which coexist with each other to be useful.
- *Expectation of the number of certain goods/resources needed for disasters such as hurricane, tornado, and earthquakes*: This can be achieved by targeting individuals (donors) in certain geographic locations, or individuals in disperse locations. Using the traits of individuals who normally donate goods/resources that are useful when a disaster takes place, and geographic locations with the maximum number of disaster-needed goods donations, the right targets would be determined.
- *Predicting potential donors who would default*: NPOs/NGOs spent time and money in calling donors and in following up calls. Donors that prove they are not reliable should be avoided in the future. To accomplish that, characteristics of defaulting donors will be identified and used to predict donors who would default in the future to avoid them.
- *Foreseeing drivers who would default or rejects a request after accepting it*: Centered around the details of those drivers who either do not show up or change their minds after accepting a delivery, a future (new) driver can be classified as either reliable or unreliable. This information can be used to improve screening of future drivers.
- *Predicting drivers who would never reject a request*: another approach for predicting the reliability of drivers is to explore the details of those drivers who have never rejected a request for delivery, and to use the outcome of this exploration to conclude if a new (future) driver would never reject any request.
- *Foretelling drivers who would be willing to drive long distance*: a number of drivers (volunteers) would not go long distance. This will result in delaying the delivery and annoying the donor. Investigating the qualities and characteristics of drivers who carried out long distance tasks will help NPOs/NGOs to determine if a certain driver would be willing to accept a long-distance delivery.

*C. Driver*

In general drivers need to see NPOs/NGOs do not default and provide accurate details on distance, and type, weight, and size of goods. Furthermore, they will be looking for reliable donors at pickup locations.

- *Predicting the NPOs/NGO's who might cancel their request at the last moment*: It is important for a driver to know if an NPO/NGO would change their mind to avoid wasting time driving to the pickup location and not taking care of their other personal obligations. This could be fulfilled by investigating the characteristics of NPOs/NGOs who have cancelled their request at the last moment and avoid accepting requests from NPOs/NGOs who reveal the same descriptions.
- *Identifying NPOs/NGOs who will not provide precise details about their request*: Drivers can anticipate those NPOs/NGOs who will not provide the accurate details about the request, such as distance, size, type of goods, etc., by scrutinizing the NPOs/NGOs who already did that. If an NPO/NGO is classified as one of these, the driver will make sure they will ask for all the details before accepting the job.
- *Anticipating donors who are most likely going to default*: Donors who have defaulted before will be aimed at to generate an understanding of their aspects. Knowing that will help drivers to avoid accepting requests from donors with those aspects.
- *Projecting donors who will change the request's location after the driver arrives at the original location:* Drivers can guess whether a donor will change the location of pickup upon arrival by probing the details of donors who have done that before. To avoid wasting time, the designated driver will be in contact with that donor to ensure the address is not changed or to obtain the new location before making the selection.
- *Expectation of the actual size of goods*: Speculating the size of goods/resources to be picked up is important for drivers. Improper size might not fit in the selected vehicle. This will result in wasting driver's time. This could be a result of the NPO/NGO not recognizing the right size (entering a wrong size), or the donor changing the size upon arrival of the driver. Both the NPO/NGO and donor causing such problem need to have their features inspected. Once their features are identified, an NPO/NGO or a donor could be classified as possible providers of the wrong size. Hence, the driver can contact either one or both to circumvent wasting time and frustration.
- *Estimation of the actual distance*: It is possible for NPOs/NGOs to make mistakes regarding the actual distance or even the nearest estimate. A driver might accept a job thinking it is a short distance, but it turns out to be a long distance once they hit the road. To avoid such situations, drivers need to seek out those NPOs/NGOs who would possibly provide the inaccurate distance. Analyzing their traits will reveal which NPO/NGO need to be consulted regarding the distance before accepting the job.
- *Predicting the jobs/requests that require heavy lifting*: Some drivers might have back, shoulder, or neck problems. They are only allowed to lift certain maximum weight. Such drivers realized that goods/resources are heavier than what they can manage when arriving at the pickup location. Dissecting the NPOs/NGOs that made drivers go through such situations helps to conclude their features. This will help drivers to elude NPOs/NGOs with similar features.

### D. Donor

Donors are concerned about reliability of vehicle and driver. In addition, the facilitating of picking up the goods is a priority for them.

- *Predicting drivers that are not reliable*: Based on the behaviors of drivers who either default, or do not arrive within the estimated time, donors can predict if a driver will not show up or arrive late. They then make their decision regarding the driver using the results of this analysis.
- *Foretelling NPO/NGO who most likely will delay picking up the donations for some time*: Donors are eager to have their donation of goods/resources be taken care off as quickly as possible. Some NPOs/NGOs might delay assigning a driver to pick up these goods/resources. By studying the peculiarities of such NPOs/NGOs, donors can guesstimate which NPOs/NGOs are most likely to reflect such a behavior.
- *Anticipating NPO/NGO who will most likely default on providing a receipt*: Receipts of donations estimated monetary value are important for donors for taxing purposes. Delaying those receipts or not providing them will upset donors. Donors will not be interested in dealing with such NPOs/NGOs in the future. Conjecturing the individualities of such NPO/NGO will help drivers to avoid dealing with those with similar characteristics.
- *Predicting NPOs/NGOs that might send the wrong type of vehicle for the size of the donated goods*: Selecting the wrong vehicle for picking up goods/resources will be annoying for both drivers and donors and a waste of time. Donors need to have their goods moved as soon as possible. Assessment of traits will help identifying those who would possibly behave in a similar fashion.

## VI. CONCLUSION

With the notion of big data analytics as the practice of exploring huge and diverse datasets with sophisticated analytic approaches and methods to reveal hidden patterns, unfamiliar correlations, and other valuable knowledge to make abreast decisions, this paper contributed by analyzing the possible potential future analytics of the GoodTurn system to allow the stakeholders; Ford, NPOs/NGOs, drivers, and donors, to make informed decisions that improve their way of doing things and save them time and money. Various potential predictions, classifications, and clustering are suggested based on the future GoodTurn big data when matured. As soon as the big data become fully established, big data analytics tools will be adopted to get the desirable knowledge and insights for decision making.

## REFERENCES

[1] W. Raghupathi and V. Raghupathi, “Big Data Analytics in Healthcare: Promise and Potential,” Health Information Science and Systems, vol. 2, no. 1, pp. 110-119, 2014.

[2] O. Y. Al-Jarrah, P. D. Yoo, S. Muhaidat, G. K. Karagiannidis, and K. Taha, “Efficient Machine Learning for Big Data: A Review,” Big Data Research, vol. 2, no. 3, pp. 87-93, 2015.

[3] H. C. Chen, R. H. Chiang, and V. C. Storey, “Business Intelligence and Analytics: From Big Data to Big Impact,” MIS Quartely, vol. 36, no. 4, pp. 1165-1188, 2012.

[4] A. L'Heureux, K. Golinger, H. F. Elyamany, and M. A. M. Capretz, “Machine Learning with Big Data: Challenges and Approaches,” IEEE Access, vol. 5, pp. 7776-7797, 2017.

[5] D. T. Nguyen and J. E. Jung, “Real-Time Event Detection for Online Behavioral Analysis of Big Social Data,” Future Generation Computing Systems, vol. 66, pp. 137-145, 2016.

[6] P. Campbell, “Editorial on Special Issue on Big Data: Community Cleverness Required,” Nature, vol. 455, no. 7209, pp. 1-1, 2008.

[7] S. Choi, J. Seo, M. Kim, S. Kang, and S. Han, “Chorological Big Data Curation: A Study on the Enhanced Information Retrieval System,” IEEE Access, vol. 5, pp. 11269-11277, 2017.

[8] G. Bello-Orgaz, J. J. Jung, and D. Camacho, “Social Big Data: Recent Achievements and New Challenges,” Information Fusion, vol. 28, pp. 45-59, 2016.

[9] J. Lin and D. Ryaboy, “Scaling Big Data Mining Infrastructure: The Twitter Experience,” SIGKDD Explorations, vol. 14, no. 2, pp. 6-19, 2103.

[10] W. Fan and W. Bifet, "Mining Big Data: Current Status and Forecast to the Future," SIGKDD Exploration, vol. 14, no. 2, pp. 1-5, 2013.

[11] X. Amatriain, “Mining Large Streams of User Data for Personlized Recommendations,” SIGKDD Explorations, vol. 14, no. 2, pp. 37-48, 2012.

[12] A. Mehmood, I. Natgunanathan, Y. Xiang, G. Hua, and S. Guo, “Protection of Big Data Privacy,” IEEE Access, vol. 4, pp. 1821-1834, 2016.

[13] B. Matturdi, X. Zhou, S. Li, and F. Lin, “Big Data Security and Privacy: A review,” China Communications, vol. 11, no. 14, pp. 135-145, 2014.

[14] E. Žunić, A. Djedović, and D. Đonko, “Application of Big Data and Text Mining Methods and Technologies in Modern Business Analyzing Social Networks Data about Traffic Tracking,” in Proc. The 2016 XI International Symposium on Telecommunications (BIHTEL), Sarajevo, Bosnia-Herzegovina, 2016, pp.1-6.

[15] I. Chih-lin, L. Yunlu, S. Han, W. Sihai, and G. Liu, “On Big Data Analytics for Greener and Softer RAN,” IEEE Access, vol. 3, pp. 3068-3075, 2015.

[16] J. Liu, F. Liu, and N. Ansari, ``Monitoring and analyzing big traffic data of a large-scale cellular network with Hadoop," IEEE Network., vol. 28, no. 4, pp. 32-39, 2014.

[17] K. Snyder and K. Daimi, “The Application of Software Engineering to Moving Goods Mobile App,” in Proc. The 2017 International Conference on Software Engineering Research and Practice (SERP’ 17), Las Vegas, USA, 2017, pp. 88-97.

[18] K. Snyder and K. Daimi, “Securing Ford Mobility System,” in Proc. The Thirteenth International Conference on Networking and Services (ICNS 2017), Barcelona, Spain, 2017, pp. 1-7.

[19] Tax Excempt World, “NonProfit Organizations in Michigan by County,” https://www.taxexemptworld.com/organizations/michigan-counties.asp, September, 2017, [retrieved: March, 2018].

[20] Ford Motors on Forbes Global 2000 Lists, “https://www.forbes.com/companies/ford-motor/,” 2017, [retrieved: March, 2018].

[21] Wikipedia, “Ford Motor Company – Number of Employees, https://en.wikipedia.org/wiki/Ford_Motor_Company, [retrieved: March, 2018].

[22] Detroit Free Press, “Michigan's population increased for the fifth straight year in 2016,” http://www.freep.com/story/news/local/michigan/2016/12/20/michigan-population-increase-census/95631726/, [retrieved: March, 2018].

[23] The Nonprofit Sector in Michigan, “Economic Impact of Michigan’s Nonprofit Sector,” https://www.independentsector.org/wp-content/uploads/2016/12/Michigan-1.pdf, [retrieved: March, 2018].

[24] Center on Nonprofits and Philanthropy, “The Nonprofit Sector in Brief 2015,” October 2015, https://www.urban.org/sites/default/files/publication/72536/2000497-The-Nonprofit-Sector-in-Brief-2015-Public-Charities-Giving-and-Volunteering.pdf, [retrieved: March, 2018].