Flight or Drive? Mining Evacuation Behaviours in 2017 Hurricane Harvey

Chenxiao (Atlas) Guo[a]*, Qunying Huang[a]

[a] Department of Geography, University of Wisconsin-Madison, Madison, U.S.A.
* chenxiao.guo@wisc.edu

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Introduction

Hurricane is recognized as the costliest natural disaster in the United States, bringing devastating impacts in coastal areas (Weinkle et al., 2018). Advances in atmospheric science have made it possible to predict the intensity and moving track of hurricanes in days, allowing people to take effective actions. Due to the effective warnings, deaths could be minimized by taking proper evacuating actions, thus more and more attention has been paid to evacuation behaviours, mainly focusing on whether, when, and where people evacuate, as well as the relevant issues.

Researchers traditionally rely on the post-event survey, which could be expensive and slow, with limited participants (Henderson et al., 2009). Traffic volume data becomes another data source, but it is centred on vehicles instead of evacuees, limiting to ground transportation only. In the recent decade, social media platform plays an important role in not only releasing guidance information such as weather and traffic, but also provides great opportunities to gather information from the public. Regarding social media, user-generated contents such as text, image, and video, along with the spatiotemporal information, provide great potentials in helping understand the evacuation patterns (Murray-Tuite & Wolshon, 2013). So far, a lot of progress has been made in answering "whether", "when" and "where" people evacuate using social media data (Martín et al., 2017; Kumar & Ukkusuri, 2018), while the transportation mode, namely, the "how" question, is still not comprehensively answered and needs further exploring.

In terms of inference of transportation mode, there are various relevant studies using machine learning algorithms, but their major data source, GPS data, is typically not available for severe disaster events, and it only covers the small-scale ground transportation. Therefore, with comprehensive consideration of scenarios at large spatial scale, social media data could be a novel data source to fill the research gap of exploring the transportation mode of evacuation behaviour during disaster events.

The study case is the Category-4 Hurricane Harvey in 2017, which is so far the costliest Atlantic hurricane (tied with Hurricane Katrina) with 125-billion-dollar loss and 107 deaths. The substantial cost is associated with its meteorological characteristics, while the Texas governor and Houston mayor ironically released opposite order towards the evacuation. Such complexity in controversial policies also evokes the need to explore the actual transportation pattern of the evacuation practices.

This research utilizes geo-tagged twitter data to generate trajectories representing the movement of evacuees during 2017 Hurricane Harvey. By considering selected spatiotemporal and semantic variables relevant to transportation, multiple machine learning models are built based on a manually recognized ground-truth dataset of transportation mode, in order to further estimate and visualize the spatiotemporal pattern of the evacuation behaviours.

Data

This research uses geo-tagged twitter data to generate the estimated evacuation trajectories. The main steps of data collection and pre-processing include: 1) initial keyword-based collection; 2) spatiotemporal filter to focus on the event; 3) manual verification of personal users; 4) second-round collection of historical data; and 5) spatiotemporal filter to set the scope.

Considering multiple perspectives, various datasets are utilized including NOAA's hurricane track, transportation-related data (U.S. domestic airports with passenger airlines, major regional bus stations), administrative unit data (state, county, core-based statistical area, urban area), and several regions of interested which are relevant to Hurricane Harvey: greater Houston area, mandatory and voluntary evacuation zones, as well as moderate and severe affected areas.

Method

The following chart shows the workflow of this research (Figure 1). With pre-processing and spatiotemporal calculation, the twitter-based point dataset is attached with additional attributes. After validation and sentiment analysis, the points are connected to trajectories representing people's movement during the hurricane. After manual inferring partial dataset as the ground truth, multiple machine learning models are built and tested, and a well-performed model is selected to predict the remaining trajectories' transportation mode. Finally, the trajectories' general spatiotemporal pattern and the transportation mode will be analysed and visualized.

The two major procedures will be further introduced, including the generation of twitter-based trajectory, and the transportation detection using machine learning techniques.

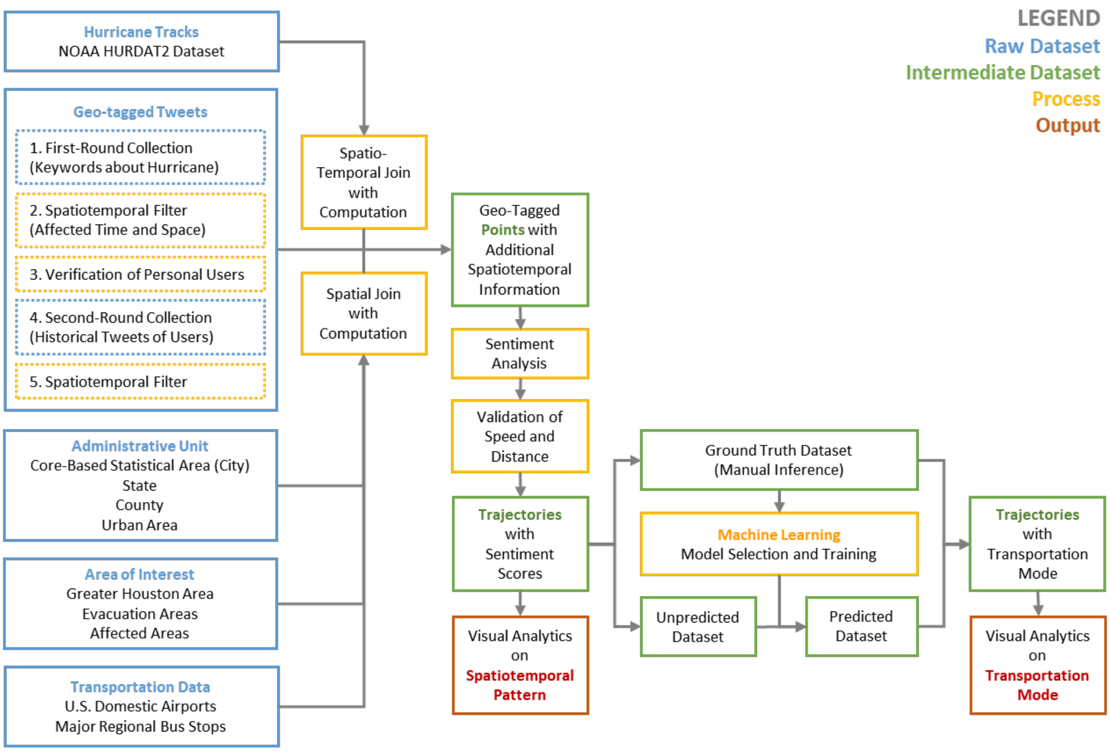

Figure 1: Workflow of research design.

Generation of Twitter-Based Trajectory

After the data collection and pre-processing steps, the geo-tagged twitter dataset is generated, which are the tweets of validated personal users in the year of 2017, who used to be living in the affected areas during Hurricane Harvey. Since the geotagged twitter data has geographic coordinates, it enables us to calculate their belonging administrative units, relationships with interested areas, as well as distances with transportation-related places (domestic airports, regional bus stops). Together with the timestamp and Hurricane Harvey's track, the distances between the tweeting location and hurricane centre are calculated, as well as the storm's characteristics at that time.

Based on the tweets' content, two relatively simple and reliable methods are used to calculate the sentiment and emotional scores, including Valence Aware Dictionary and sEntiment Reasoner (VADER) and Linguistic Inquiry and Word Count (LIWC). To assist the further steps of transportation mode detection, over 100 keywords relevant to flight and ground transportation are checked in all the tweet content.

Additionally, since twitter does not prevent users to attach fake locations, the invalid trajectories are marked with either no moving distance or speed of over 600 mph, the max cruising speed of most commercial passenger aircraft. After checking all the temporally adjacent tweets of the same users, the dataset of twitter-based trajectories is generated by connecting the lines between all the two temporally successive locations for individual validated users.

Machine Learning in Transportation Detection

In this research, only two basic transportation modes are considered: flight and ground (drive) transportation. The specific type of ground transportation is not distinguished, and water transportation is not considered either. Additionally, the third type of transportation mode, the "unknown" type, is defined where the transportation mode cannot be easily recognized based on the existing information.

The ground truth dataset is assigned by manual inference of a random subset of 2284 trajectories, with the help of some pre-generated assistant variables, such as moving distance, speed, id and distance to the nearest airport, distance to nearest regional bus stops, and whether individual transportation-relevant keyword is detected. Practically, the meaning of tweet content plays an important role in recognizing the transportation mode in this training dataset, and some trajectories have to be labelled as "unknown" even with manual interpretation.

To learn the pattern from the ground truth data of transportation mode, several widely used supervised machine learning models are considered to conduct the classification: nearest neighbours, Naïve Bayes, support vector machine (SVM), decision tree, random forest, adaptive boosting (AdaBoost), quadratic discriminant analysis (QDA), and artificial neural network. These models will be tested with a split of 70% training dataset and 30% test dataset, with a 10-fold cross-validation process. Besides the average accuracy, it is also expected that the result of critical features should be relatively understandable and easy to be interpreted. Once the model is specified, it will be used to infer the transportation mode of all the other valid trajectories.

Results

After testing of the considered machine learning models, the decision tree model is selected due to its satisfactory performance (96.50%) and characteristics of interpretable result (Table 1). The confusion matrix and classification report of the selected decision tree model is listed in Table 2 and 3. With further tuning using grid search method, the model is finalized with an accuracy of 96.9%, and based on which the transportation mode of 88950 unlabelled trajectories are predicted.

Model	Average Accuracy (%)
Decision Tree	96.50%
AdaBoost	94.54%
Random Forest	93.82%
Naive Bayes	92.01%
Nearest Neighbours	89.25%
Neural Network	82.16%
SVM	81.40%
QDA	79.52%

Table 1: Performance of compared machine learning models.

	Predicted Flight	Predicted Unknown	Predicted Drive
Actual Flight	57	7	1
Actual Unknown	1	27	2
Actual Drive	1	8	555

Table 2: Confusion matrix of selected decision tree model.

	Precision	Recall	F1-Score	Support
Class: Flight	0.97	0.88	0.92	65
Class: Unknown	0.64	0.90	0.75	30
Class: Drive	0.99	0.98	0.99	564
Accuracy	-	-	0.97	659
Macro Avg	0.87	0.92	0.89	659
Weighted Avg	0.98	0.97	0.97	659

Table 3: Classification report of selected decision tree model.

The following selected figures visualize the aggregated trajectories of different transportation modes, as well as the analytics of spatiotemporal patterns relevant to transportation mode (Figure 2 to 5).

Since this dataset is focusing on Hurricane Harvey, intense connections are detected centring at the city of Houston, with aggregated flight trips to many U.S. big cities, and drive trips to nearby local cities (Figure 2). When zooming in to Hurricane Harvey spatiotemporally, at the same time considering the moderately and severely affected areas, Houston has many connected drive trajectories with nearby satellite cities and regional cities (Figure 3).

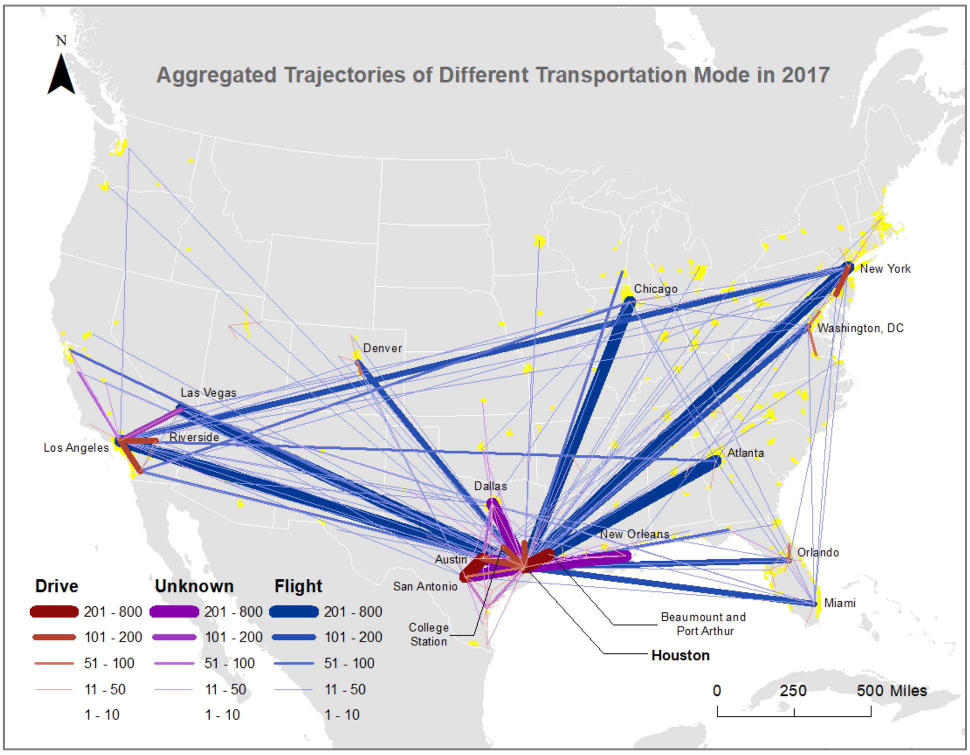

Figure 2: Aggregated trajectories of different transportation modes in entire dataset.

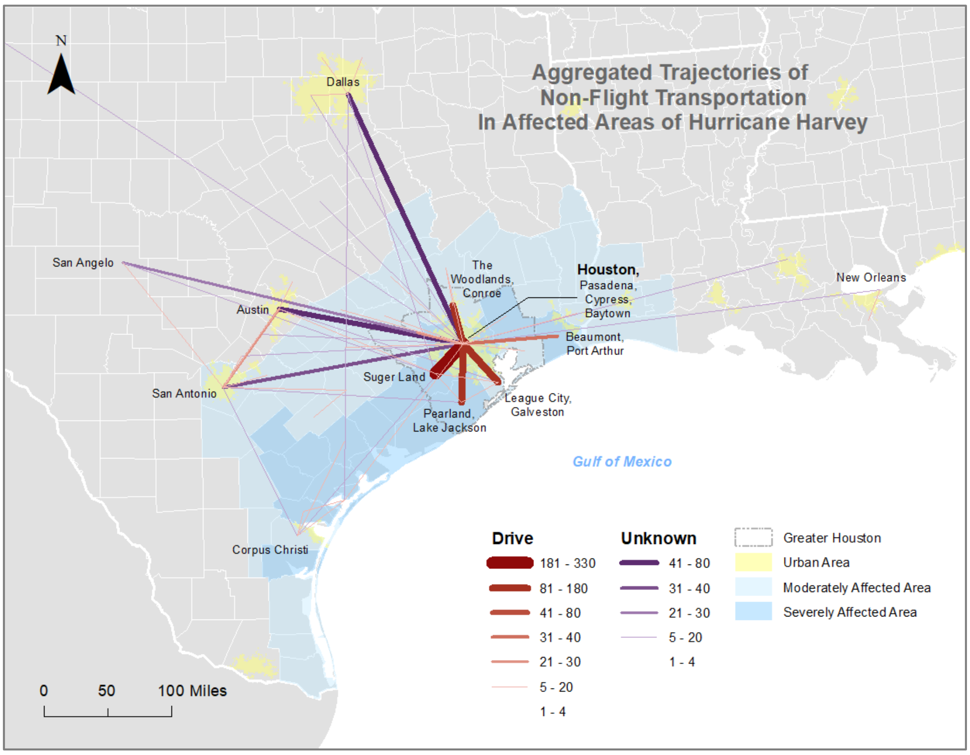

Figure 3: Aggregated non-flight trajectories in affected areas of Hurricane Harvey.

In terms of temporal change, both flight and drive transportation witness a drop during Stage II, when Hurricane Harvey got increasingly stronger before making landfall, while the short-distance drive transportation got much lower (Figure 4). Regarding the sentiment, trajectories in both flight and drive transportation got lower scores (which means more negative) during this event, while the driving users are much worse, especially in Stage III, when Hurricane Harvey made landfall, bringing a huge amount of precipitation in Houston Area (Figure 5).

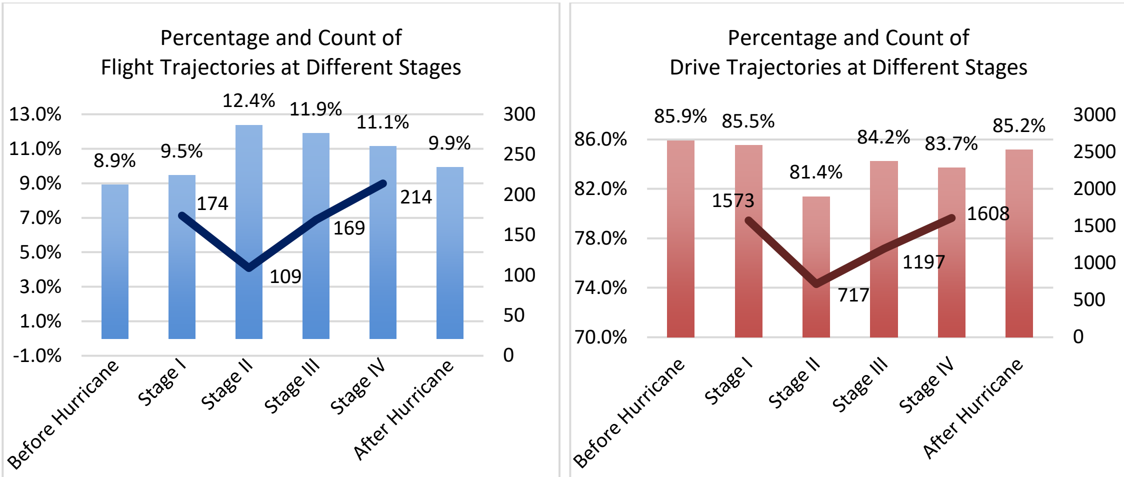

Figure 4: Comparison of flight (left) and drive (right) trajectories at different stages.

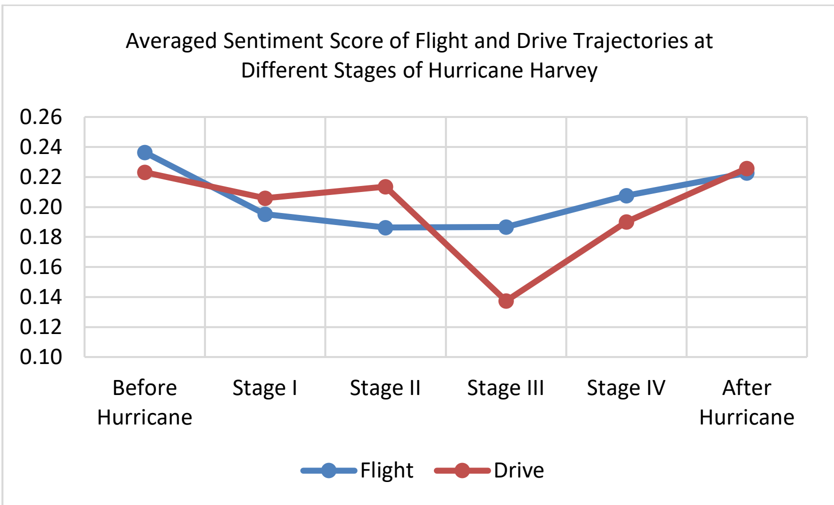

Figure 5: Averaged sentiment score of flight and drive trajectories at different stages.

Discussion and Conclusion

This research utilized geo-tagged Twitter datasets to draw a picture of evacuation behaviours during disaster focusing on transportation mode detection. Specifically, a framework is proposed to generate trajectories of verified affected users, detect the transportation mode based on various variables using machine learning algorithms, and further analyse the spatiotemporal pattern of these users' movement.

This twitter-based research, as well as other studies using social media data, has an assumption that the twitter user could be regarded as a sample of actual population, but apparently, it could be highly biased. Also, the availability of twitter might be affected by disaster events, which introduces another uncertainty. Furthermore, twitter-based locations are only a subset of reality, bringing more potential issues.

Besides these limitations, this approach is still worth exploring. In the future, the geotagged twitter data could be deeper mined to reveal more semantic information such as the discussed topic, awareness of the situation, thus assisting the transportation mode detection. Also, user-level inference and analysis are worth exploring, providing clearer user portraits in the context of natural disasters. Further studies also include the comparisons among multiple data sources, finer category of ground transportation mode, as well as the applications in more complicated multi-event scenarios.

To conclude, this research provides an applicable approach for natural disaster management to better understand the evacuation behaviours, especially the transportation mode.

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