Modeling Human Decision-Making during Hurricanes: From Model to Data Collection to Prediction

Extended Abstract

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ABSTRACT

Hurricanes are devastating natural disasters. To effectively plan to help people at risk during a hurricane, a model of human decision-making is needed to predict people's decisions and to potentially identify ways to influence those decisions. In this work, we propose a generative model of human decision making based on a Markov Decision Process where we explicitly model concerns, risk perception, and information. As a first step toward evaluating the model, the work presented here focuses on one step of the decision part of the model. We created a questionnaire based on the model and collect data from 2018 Hurricanes, Florence and Michael. The results show that, across hurricane data-sets that we collected, the features of the models correlate well with evacuation decisions and our model outperforms existing methods in most cases, demonstrating the validity of the proposed model.

KEYWORDS

Modelling for agent-based simulation; Validation of simulation systems; Decision-making during hurricanes

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1 INTRODUCTION

Hurricanes, one of the most devastating natural disasters, have increased in frequency and intensity in recent years. In the past two years, there have been at least five major hurricanes affecting the United States including Hurricane Harvey, Irma, and Maria.

To help mitigate damage and casualties, effective and efficient evacuation and emergency management plans are needed. The crucial part of such plans is an ability to predict and influence human decision-making and behavior during hurricanes. One way to achieve this is to build a model of human decision-making that can predict decisions accurately, can also explain the decisions and, thereby, can identify how decisions could be altered.

There has been much existing research on hurricane evacuation behavior [2], [4], [5], [6]. These studies mainly focus on identifying features that are significantly associated with the decision to evacuate or stay. They found that concerns, risk perception and information about the hurricane play important roles in the decision. However, other demographic characteristics have either minor or inconsistent effects on evacuation decision. On the other hand, existing Agent-Based Models or decision models are mainly in the form of either decision tree or different variants of logistic regression [3], [7], [8], [9], [10].

The main limitation of these models is the lack of the ability to explain the decision and to model the sequential nature of hurricane event that can last days from forming to landfall. To this end, we propose a generative model of human decision based upon a Markov Decision Process (MDP) which is a general framework for sequential decision making under uncertainty. MDPs allow us to model concerns and risk perception that should help explain the decision. We extend the MDP to include how people may look ahead to consider future information. In this work, we focus on evaluating the predictive ability of one step of its decision procedure using questionnaire data from states affected by Hurricanes Florence and Michael. The results show that our model outperforms other existing methods, both in term of validation error within each dataset and testing error using the other hurricane.

2 MODEL

Based on existing human studies, personal concerns and risk perception play important roles in evacuation decisions. In addition, these features could be influenced by not only household characteristics but also prior beliefs about hurricanes and information received from officials and social channels. This led us to build a model centered around capturing the notion of concerns and risk perception as well as information and change of beliefs.

The model is based on an MDP. An MDP is a tuple, (S, A, T, R, γ). State (S) is a sufficient statistic of what occurred in the past, such that what will occur in the future only depends on the current state, satisfying the Markov assumption. In the model, a state is represented by a set of features. There are two types of state feature. The first one is reward-based features representing concerns that people may have. There are three important concerns: safety, money, and experience. Potential experiences during a hurricane are living in a flooded house, living without electricity, and living in a shelter. The second one is transition-based features representing an agent's beliefs about the state of the world, in this case, the impact of hurricane. They describe how reward-based features will change and can be viewed as risk perceptions. There are two related transition features for money: cost to travel to some place safe and cost to stay at some place safe. For safety concern, the transition-based

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feature is the probability of being safe if staying at home during the hurricane. For experience concerns, there is the flood condition and the electricity condition.

Action (A) is a set of actions available to an agent. For each state in the hurricane event, there are two main actions: evacuate or stay. Transition Probability (T) $P(s'|s, a)$ determines how actions change the features of the current state based on transition-based features. Reward (R) is a function which determines the reward (or utility) of a given state. Discount factor ($\gamma \in [0, 1)$) is a discount rate which discounts the future reward at time t by a factor of γ^t.

The model has two steps, make a decision using current beliefs and update beliefs based on new information. The current work focuses on the evaluation of the decision-making, leaving evaluation of the belief update for future work.

In the decision making, we focus on the expected utility calculation for each action in term of money cost. The cost of evacuation is the sum of safe place cost, traveling cost and noise. The cost of staying is the sum of flood cost, electricity cost, safety cost, and noise. Each cost is based on the expected outcome of corresponding condition. The action that yields lower cost is the action that the model predicts the person will do.

3 QUESTIONNAIRE AND DATA COLLECTION

The questionnaire has 4 types of questions: 1) demographic features questions that are mainly about demographic information and official notices, 2) decision specific questions including previous experience and decisions that participants made, 3) information questions about the content people received from your family and friend and from news and 4) model-based questions which focus on estimating transition probability and utility.

For these latter transition-related questions, we either ask participants what they think will happen or how likely it is that certain events will happen. Examples of these questions are: How high (in feet) did you expect your house to be flooded? What do you expect it would cost to travel to a safer place?

For utility-related questions, the main concern is on the utility associated with specific experiences. In order to measure this utility, we ask participants how much would you pay not to experience a certain event such as living in a flooded house or without electricity. We did not ask participants for money equivalent of not being seriously injured (safety cost) since it would be hard for participants to answer meaningfully. Instead, we opt to estimate it from data.

To collect the data, we used Amazon Mechanical Turk service to send out questionnaires to participants in states in the path of a hurricane. We collected data from two recent hurricanes: Florence (NC and SC) and Michael (GA and FL). This resulted in three datasets: pre-Florence with 356 responses, post-Florence with 684 responses, and post-Michael with 542 responses. We did not collect pre-Michael because of the brief period between forming and making landfall.

4 MODEL FITTING

To fit the model using the data, we ignore the experience of living in a shelter because there was not enough data of people evacuating to shelters. Thus we only need to fit safety cost and noise term. Noise represents other concerns that we did not include in the model. Other parameters in the model are instantiated using the answers from the questionnaire.

We test two methods of fitting. The first is grid search. Essentially, we exhaustively search through a specified range of parameters to find a value of parameters that achieve the lowest classification error. The second method used Bayesian Inference. To apply Bayesian Inference, we need to convert expected utility of each action to the probability of choosing each action. To do so, we apply a softmax function to calculate the probability of selecting each action. We implement Bayesian Inference using Stan [1].

In addition to assuming that a value of parameters is the same across the whole population, we explore the idea that different groups of people may have a different set of value of parameters. For grid search, this is a straightforward to realize by simply dividing the data into smaller batches based on the group and estimate the value of parameters independently for each group. To estimate group parameters in Bayesian Inference, we use the Hierarchical Bayesian model.

5 EVALUATION AND RESULTS

To evaluate our model performance, we compare it with two additional methods namely decision tree and logistic regression. For both methods, we test their performance based on different sets of features. The features sets are demographic features only, model-based features only, and demographic, model-based, information, and previous decision all together as the last set.

To evaluate our model predictive and generalization ability, we test our models and other methods in two different settings. The first setting is to train and test on the same hurricane dataset using 10-fold Cross-Validation to calculate performance measurements. The other setting is to train on one dataset and test on other datasets. The test sets are either post-Florence or post-Michael.

Overall, our model achieves better results compared to other existing methods in most cases for within datasets. The model achieves as low as 5.5% error rate for post-Florence and at about 8% for post-Michael. However, the model and other methods do not perform well for pre-Florence achieving around 20% error rate. This may partly due to the fact that we asked them to rate on the likelihood scale instead of what they may plan to do. In term of performance across datasets, our model achieves better results than other methods in all cases. Using one hurricane's post data to predicting another hurricane's post data achieves better results than using pre-hurricane data in all cases. [1]

The results also suggest that model-based features and prior experiences are important features and better than demographic features in achieving a good prediction. In addition, most model-based features correlate well with evacuation decision across all three datasets further supporting the predictive ability of the model.

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[1] All codes, questionnaires, summary of data, and additional results can be found at https://github.com/yongsa-nut/HurricaneFirstPart

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