Thesis Proposal:
A Computational Model of Emotion Influence on Beliefs and Desire

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Abstract

Coping and emotion regulation is foundational for many aspects of human life, yet computational model on this topic is still lacking, especially one that is evaluated using data from real events. In this work, I propose to build a computational model of emotion focusing on how people cope and regulate their emotion, specifically how people change their beliefs and desires or goals. The model assumptions and construction are driven by existing psychological theories including Lazarus's Appraisal and Coping Theory, and Gross's Emotion Regulation Theory. The representation of the model is Markov Decision Process Framework, a general framework for modelling sequential decision-making. The model will be evaluated in two ways. The first way is a simulation study of fox and sour grape story. The second way is based on empirical data on the hurricane decision. The empirical data will include questionnaire data from real hurricanes and control experiments.

1. Introduction

Consider children decide to have fun by playing a game of chess. Some may care about winning more than others, but most if not all children want to win. Those who win will celebrate, share a story with others, or ask to play again. Those who lose may flip the table, go practice and study more, stop liking chess and go do something else, or ask to play again.

Consider another example, a hurricane evacuation decision. This is a life-threatening decision. People have to decide whether to evacuate or stay. Evacuation can cause a lot of money or stuck in the public shelter. Both of these outcomes can incur a strong negative feeling. On the other hand, people who stay may risk their life or stuck in flooded house without electricity and limited supplies of food and water. These outcomes, again, can incur a strong negative feeling. Some people may value their money more, believe that they are in control of the situation and/or perceive the risk to be lower and decide to stay. Other may value their life more, overestimate the risk, and/or value their money less and decide to evacuate.

From these two examples, one can see that emotion plays an integral role in decision-making. People consider emotional consequences of decision outcome. Emotions signify things that are important to us or things that we want to avoid. Emotions influence our decision-making about things in the past, present and future. People seek to feel good and avoid feeling bad like children who want to win and people who evacuate from hurricane to feel safe. We feel sad and may cry when we lost something important. When being emotional, people find a way to increase and prolong good feeling but they try to reduce and subdue bad feeling. As the two examples illustrated, they could achieve this by directly changing the situation itself such as flipping the table, or by the way they think about the situation such as changing how important wining is.

Decisions can involve multiple consequences that impact people differently. These consequences can range from immediate to future. We can decide what to do not just now but also in the future. As a result, any decisions could involve considering near and far future consequences of a sequence of actions. Therefore, decision-making is sequential in nature and emotion could influence how we consider these different consequences.

With how important decisions are to our life and how emotion influence decisions, understanding how people decide with respect to their emotions is an important scientific goal. Understanding these relation will allow us to accurate prediction of people's decision and find ways to influence decision. These can lead to many useful and important applications. For instance, this could lead to better and more effective plans for evacuation management during the hurricane. Another example is to help people who are addicted to drug or other substance change their behaviors.

To this end, I propose to build a computational model that unifies the relationship between emotion and decision focusing on how people deal with emotions. The model will be constructed based on existing psychological theories that link emotion and decision together and a general sequential decision framework, Markov Decision Process (MDP). Psychological theories include appraisal theories, coping theory and emotion regulation theory. MDP is a widely-used framework for building an agent in reinforcement learning.

There are two main goals of the model. The first one is to explore different ways of describing different actions that people use to deal with emotions and the situations that cause them. Following this goal is to evaluate the model's predictions and its ability to capture the real situation. The model is evaluated in two board ways: simulation study and empirical evaluation. The simulation study is to demonstrate that the model could explain existing phenomenon and examples and explore different ways of describing the importance components of the model. The selected situation is the story of Fox and Sour Grape.

The empirical evaluation evaluates the model's predictions using experimental data. The chosen situation is hurricane evacuation decision, because it is an important domain and it is an emotional rich situation. As stated earlier, an accurate model of human decision-making during the hurricane is a necessary component for coming up with effective and efficient evacuation management plans to help mitigate damage and casualties. Predicting how people deal with the situation is the main focus of the evaluation of the model. In this work, we focus on two important aspects of hurricane event that are related to emotion: 1) concerns that people may have and the beliefs about the hurricane and 2) the information on hurricane and how people take these information into account when making the decision.

The computational model of emotion is not a new topic. Existing works have proposed many ways to model emotion ranging from ad hoc to basing on various emotion theories. A review of existing computational models of emotion can be found at literature review section. The novel contribution of the proposed model is the formulation of the coping and emotion regulation, changing beliefs and desires or goals, within the decision framework and the empirical evaluation specifically on the quantitative prediction of the formulation. Figure 1 shows the overall flow of the propose work.

The proposal is organized as follows. The second section is on related works from both psychological theories and existing models. The third section is about the main assumptions of the model. The fourth section is on model descriptions which build upon the assumptions. The fifth section details the simulation study. The sixth section details the empirical evaluation. The seventh section is the schedule of this work and the eighth section is the conclusion summarizing the proposed work.

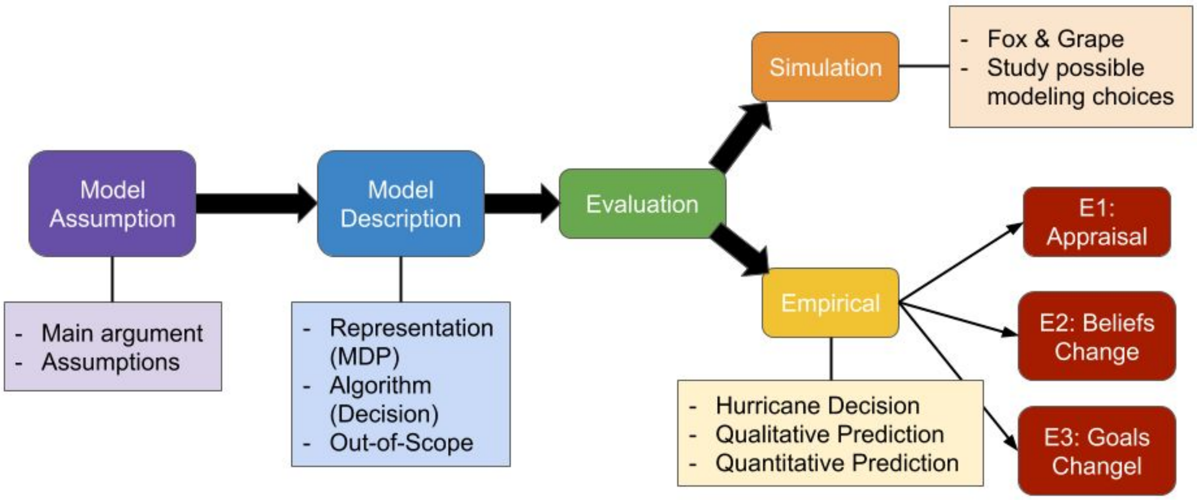

Figure 1. The overall flows of the work starting from the construction of the model which includes model assumption and model description. Following the construction of the model is the evaluation which composes of simulation study of the Fox & Grape story and empirical study on hurricane decision.

2. Literature Reviews

In this section, I review essential literature relating to the work. These include emotion theories and existing computational models.

2.1 Emotion Theory

In this section, we review three important emotion theories behind the proposed model. These three are Appraisal theory, coping theory and emotion regulation.

2.1.1 Appraisal Theories

Appraisal is a process of subjective assessment of the situation for well-being based on a person's goals and beliefs. Goals includes individual's concerns, needs, attachments, and values. They include everything that an individual cares about. Appraisal theories characterizes a situation into different dimensions or variables. Most theories include the following variables goal relevance, goal congruence (which refer to the relevance and congruence of situations for goals), certainty, agency (who cause the situation), and coping potential or control. Some appraisal theorists also propose the following variable: novelty, expectancy, urgency, intentionality, legitimacy, fairness, and norm. Thus appraisal is a process by which values are produced for these appraisal variables for a given situation.

Some appraisal theorists further argue that appraisal determines the intensity and quality of action tendencies, physiological responses, behavior, and feelings. As a result, appraisal elicits or causes emotions. [Moore 2013]

There are five major appraisal theories. The first theory is Lazarus's Appraisal theory [Lazarus 1991]. This theory separates appraisal into two basic types: primary and secondary. Primary appraisal concerns whether something of relevance to the person's well-being has occurred. Primary appraisal components are goal relevance, goal congruence and type of ego-involvement. Secondary appraisal concerns coping options which is about what any given actions can do to change the situation into a better one in terms of well-being. Three secondary appraisal components are blameworthiness, coping potential, and future expectations. The proposed model are built upon the Lazarus theory.

The second theory is Ortony Clore and Collins' appraisal theory (OCC) [Ortony et al. 1990]. This theory is a descriptive appraisal theory that proposes a way to category different situations into twenty-two board set of emotional experience types based. It helps explain the relation between appraisal dimensions and the emotion that they elicit. OCC identifies emotion into three center sub-groups: event-based, agent-based and object-based emotion. OCC also separate appraisal dimensions into two broad types: global and local. Global dimensions (variables) affect intensity of all emotion, while local dimensions are specific for particular group of emotion. Global dimensions includes sense of reality, proximity, unexpectedness, and arousal. OCC is one of the most popular theories that is used for the computational model.

The third theory is by Nico Frijda [Frijda 1986]. The unique thing about this theory is the focus on Action Tendency or Action readiness which is states of readiness to execute a given kind of action, which is defined by its end result aimed at or achieved.

The fourth theory is Roseman's appraisal theory [Roseman, 2001]. This theory argues that the different intensities of each component influence which emotions are elicited. Another unique thing about Roseman's theory is the emphasis on the importance of accountability. The fifth and the last theory is Schere's component process model [Schere, 2001]. This theory is based on the assumption that emotions are elicited and differentiated by the results of the individual's evaluation of events according to a set of appraisal criteria or sequential stimulus evaluation checks.

2.1.2 Coping Theory

There are two widely used definitions of coping. The first definition according to [Lazarus and Folkman 1984] is that "coping is constantly changing cognitive and behavioral efforts to manage specific external and/or internal demands that are appraised as taxing or exceeding the resources of the person." Figure 2 shows the overview of coping and appraisal theory by Lazarus which the main coping theory that the model built upon. The second definition according to [Compas et al., 2001] is that "coping is Conscious and volitional efforts to regulate emotion, cognition, behavior, physiology, and the environment in response to stressful events or circumstances."

Both definitions highlight coping as a controlled and effortful process. However, Lazarus and Folkman (1984) emphasize cognitive appraisals of a situation as causes of coping responses. On the other hand, Compas et al. (2001) focus on objectively stressful situations in the environment as causes of coping responses.

The Lazarus and Folkman model incorporates two broad types of coping that differ based on the focus and goals of coping efforts: problem-focused coping and emotion-focused coping. Problem-focused coping are actions that attempts to resolve the source of stress by changing the situation. Emotion-focused coping are actions to alter one's emotion via changing one's goals, beliefs or intentions which results in appraisal of the situation. Figure 1 shows the process view of coping and appraisal theory proposed by Lazarus.

The Compas' coping theory is based on a control-based model of coping that includes primary control coping, secondary control coping, and disengagement coping. [Compas et al. 2017]. Primary control coping is actions to directly change the source of stress including problem solving and emotional expression. Secondary control coping is actions to adapt to the source of stress including acceptance and cognitive reappraisal. Disengagement coping is about actions to orient away from the source of stress including avoidance or denial. In this work, we follow Lazarus' coping theory as it links to the appraisal theory.

Major coping strategies includes acceptance, cognitive reappraisal, emotional expression, problem solving, distraction, avoidance, denial, emotion suppression, and wishful thinking.

One note on coping is that coping is not just about stress but also about emotion. Lazarus [Lazarus 1990] has argued that stress is a part of emotion and we should move away from measurement of stress toward the measurement of emotion. His appraisal theory, orginiallay for stress, eventually move toward the larger rubric of emotion because it includes both positive emotions and stress-induced emotions. Therefore, in this work, we use the term coping and emotion regulation interchangeably in this work.

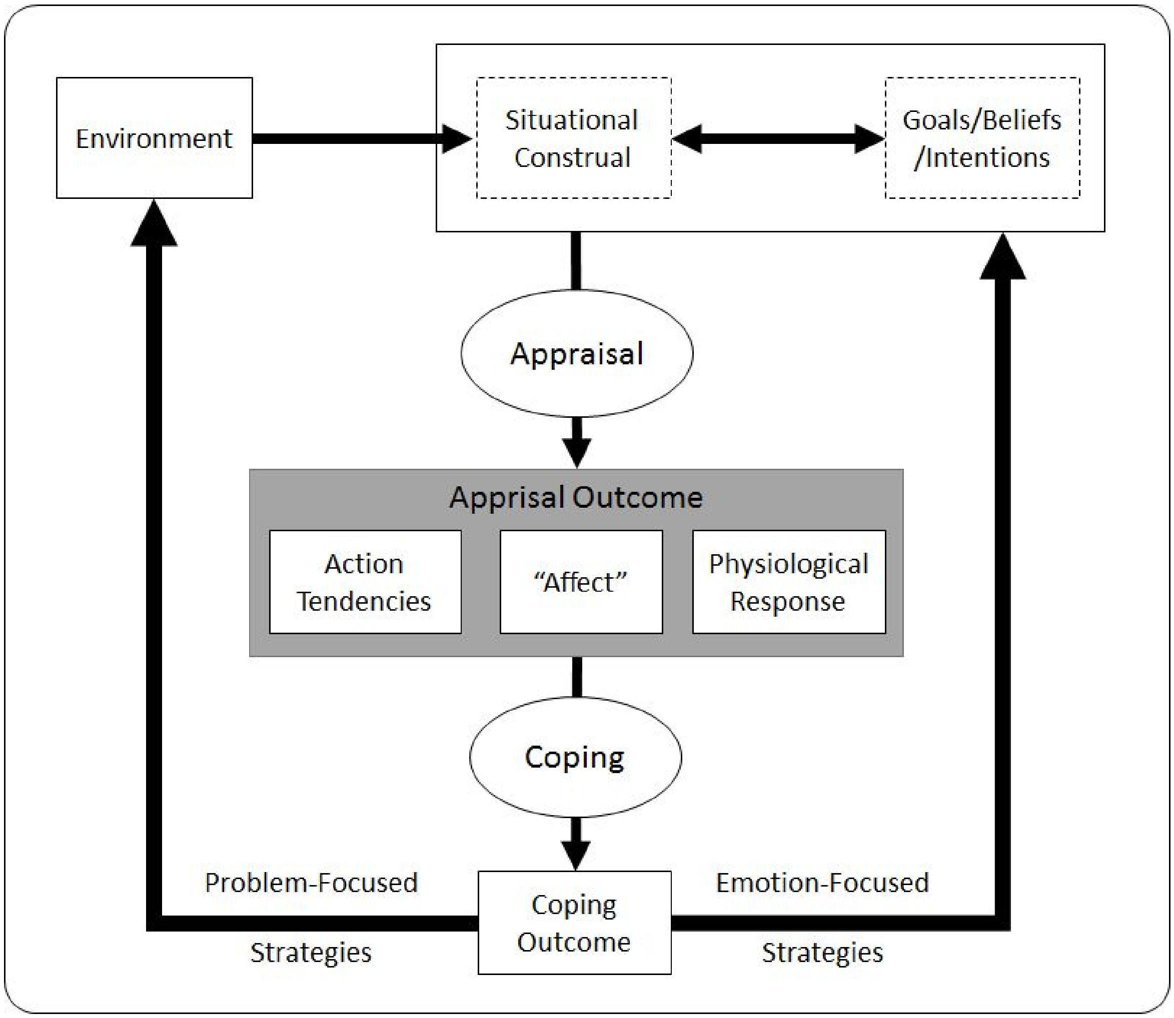

Figure 2: A process view of coping, adapted from Smith and Lazarus (1991)

2.1.2 Emotion Regulation

Emotion regulation is one of the most highly studied topics in the emotion in the recent decade. In 2013 alone, Google Scholar indexed more than 10,000 papers on emotion regulation [Gross 2015]. The most commonly used framework for studying emotion regulation strategies is proposed by Gross (1998). According to Gross (1998), emotion regulation refers to attempts to influence which emotions one has, when one has them, and how one experiences or expresses these emotions. The defining feature of emotion regulation is the goal to modify emotion trajectory. Emotion regulation can either up-regulate or down-regulate emotional experience including intensity and duration.

The process model of emotion regulation by Gross is shown at Figure 3. The process model specifies the sequence of steps involved in emotion regulation. Each step in the model is a potential target for regulation.

There are five types of emotion regulation strategies: situation selection, situation modification, attentional deployment, cognitive change, and response modulation. Situation selection refers to taking actions that make it more or less likely that one will be in a situation where one expects to experience desirable or undesirable emotions. Situation modification refers to taking actions that directly change a situation in order to change its emotional experience. This is the same as problem-focused coping in Lazarus coping theory. Attention deployment refers to directing one's attention to influence one's emotional experience. Cognitive change refers to changing one' appraisal of a situation in order to alter its emotional experience. Response modulation refers to directly influence experiential, behavioral, or physiological components of the emotional response after the emotion is well developed.

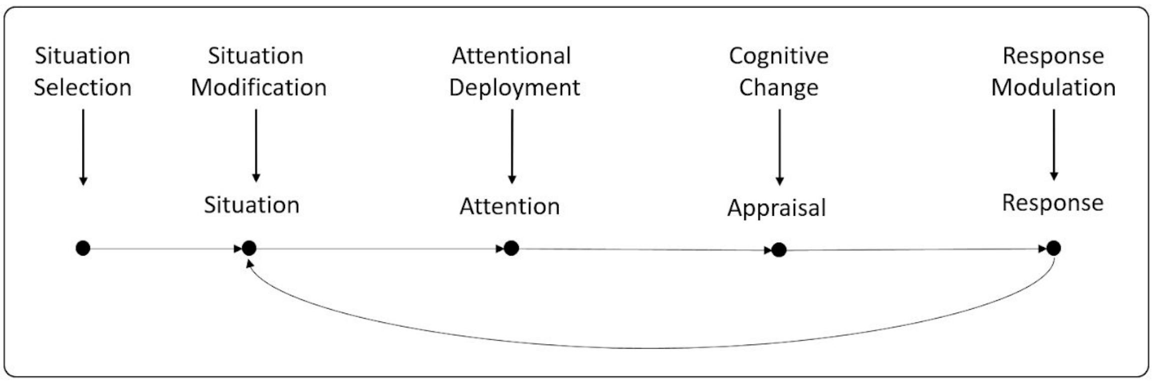

Figure 3: The process model of emotion regulation, adapted from Gross (2015)

Recently, [Gross 2015] has proposed the extended process model of emotion regulation. The extended model starts with the idea that emotions involve valuation: good vs bad for me. Figure 4 shows the extended model.

In this scheme, the "W" (world) refers to the internal or external world. The "P" (perception component) refers to a perception of whatever that valuation system is suppose to observe. The "V" (valuation component) refers to an evaluation of that perception. More specifically, valuation involves the comparison between a representation of the world and a representation of a desired state of the world (a goal state). The "A" (action component) refers to the action impulses generated by that valuation with the aim of reducing the gap between the perceived state of the world and the goal state. Some of these actions may change internal world while others may change the external world.

Many different valuation systems are typically active simultaneously and each one is for different aspects of a particular situation. In addition, multiple valuation system can interact with one another. This is a core idea for the extended process model of emotion regulation. .

According to this model, emotions are instantiated by valuation systems. Emotion regulation occurs when one valuation system (a second-level valuation system) takes another valuation system (first-level valuation system which is generating emotion) as a target and evaluates it either negatively or positively, activating action impulses that are intended to change the first-level valuation system. This description is well aligned with the definition of emotion regulation as a goal to influence the emotion trajectories.

In general, there are five ways the second-level valuation system can influence the first-level valuation system that is generating emotion. As shown in Figure 4, these include (a) taking steps to change the situation to which one will be exposed, (b) changing one or more relevant aspects of the external world, (c) influencing which portions of the world are perceived, (d) altering the way the world is cognitively represented, and (e) modifying emotion-related actions.

In particular, situation selection and situation modification refer to changing the external world to which one is exposed, attentional deployment refers to changing the perception of the world, cognitive change refers to altering the way the world is cognitively represented, and response modulation refers to modifying the actions that are activated by the emotion.

In conclusion, both Lazarus's coping theory and Gross's the process model of emotion regulation emphasise on actions that can either change one's internal model of the world (emotion-focused coping and reappraisal) or the actual external world (problem-focus coping and situation selection & modification).

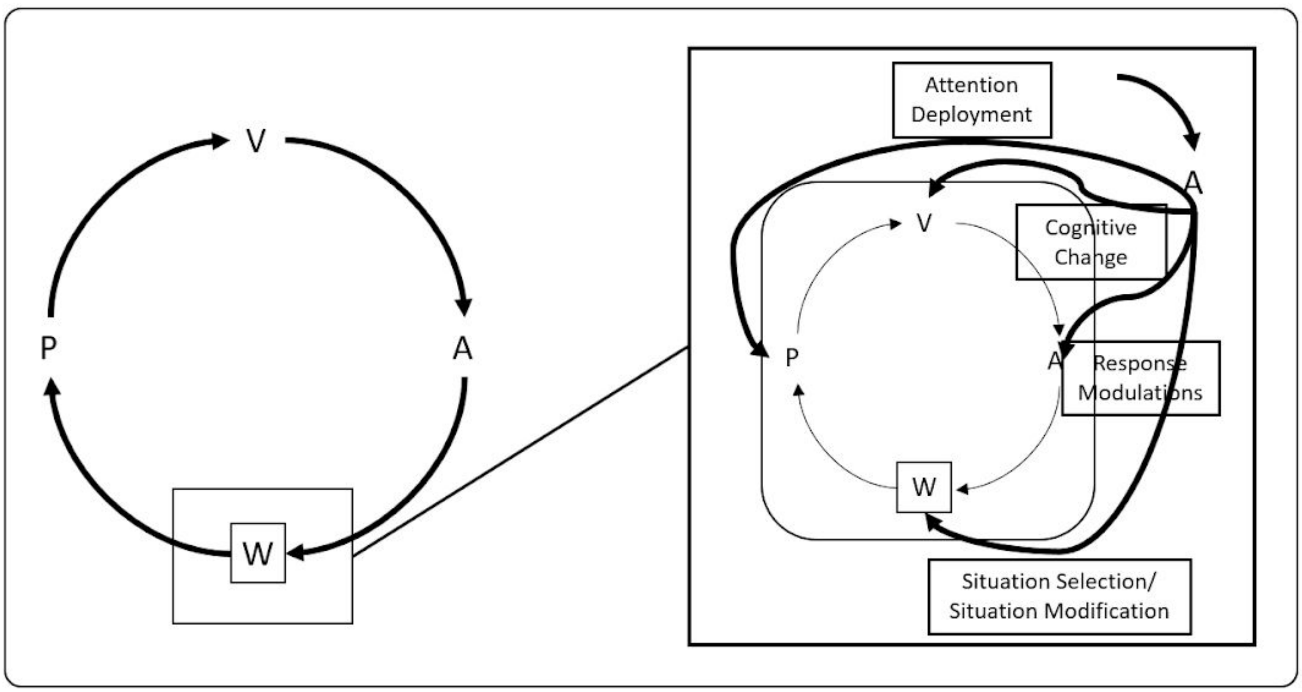

Figure 4: An extended model of emotion regulation strategies. Adapted from Gross 2015. Emotion regulation is an action that influence emotion by changing 1) the world, 2) the perception of the world, 3) the way the world is cognitively represented, and 4) responses. As shown in the inset, the second level of the cycle's actions represent 5 different emotion regulation strategies.

2.2 Computational Models of Emotion

There are many agent-based model (ABM) and multi-agent simulation that integrate emotion into the model. Below, we detail how emotions are representations and used in agent-based model.

A recent survey by [Bourgias et al 2018] has proposed to look at existing models in term of how emotions are represented and how emotions are used. In terms of how emotions are represented, there are three major ways. The first way is to represent an emotion as a simple numerical value indicating for its intensity. For example, an agent has a fear emotion represented by a value between 0 and 1 where 0 means no fear and 1 means terrified. Some works also represent duration of emotion in addition to intensity with numerical value. These numbers could be represented separately or in a vector form in the case of multiple emotions. Examples for the models are by [Ta et al. 2016], [Tsai et al. 2010], [Adam et al. 2010], [Zoumpoulaki et al 2010].

The second way to represent emotion is to use a dimensional space characterized by pleasure, arousal, and dominance (PAD space). Examples of this representation are by [Schweitzer & Gracia 2010] and [Rincon et al. 2016].

The third way is to use symbolic representation. In this way, emotion is represented by a name, various numerical values and the process to determine emotions such as rule based. This representation allows emotion to be linked to a situation that gives rise to the emotion. Examples of this representation are [Mareiro et al. 2010] and [Henniger et al. 2003].

In terms of how emotion are used, there are four major ways. The first one is reactive creation. Emotions are defined as dynamic variables of the agent and get updated directly from the perception of given events by manually defined rules. If the emotion intensity is above a certain threshold, then the agent’s behavior is modified. However, this reactive creation of emotion does not rely on any emotion theory. Examples for this type of model are by [Le et al. 2010] and [Lou et al. 2008]

The second way of how to use emotion is fuzzy appraisal using fuzzy logic rules to model the creation of emotions. Similar to reactive creation, fuzzy rules does not based on any existing psychological theory of emotion. Fuzzy sets are used to define the perceptions of an agent and fuzzy rule is used to transform them to emotions. These emotions are then used to modify the agent’s behavior. Works that have used fuzzy logic include [Kazemifard et al. 2011] and [Jones et al. 2011]

The third way is to rely on cognitive appraisal theories. Emotions are the results of the appraisal of the situation and not directly from a just perception. Majority of the model use OCC model for the appraisal of the situation. The vector of emotion’s intensity is modified by a vector representing an event and a matrix indicating the weight of personality trait over a particular component of the emotional vector. Examples of the model that use appraisal theory are [Dias & Paiva 2013], [Silverman et al. 2006], [Zoumpoulaki et al 2010].

The fourth way is the dynamics of emotions, specifically how emotions evolve over time. The model in this line of work consider that agents start with a set of emotions, and they focus on the changes of these emotions over time and the consequence of these changes on the agent’s behavior. The idea has been mainly focused by the model for the evacuation of a building or small space. [Ta et al. 2016], [Adam et al. 2010], [Tsai et al. 2011] The emotion intensity is dynamically changed based on the proximity of danger, the emotional contagion from other agents, and also a decay in time. The agent's behavior depends on the level of emotion's intensity.

Overall, from agent-based modelling and multi-agent simulation, researchers have already used and developed many different ways to handle emotions. However, one thing that stands out is that many models determine the influence of emotion to decision or action in an ad hoc way or manually and most if not models do not include any notion of coping or emotion regulation to deal with the emotions. One reason behind the simplicity is that most of the works from ABM focus on large scale simulation that does not permit a lot of computation for a more complex decision-making.

2.2.1 Existing Models of Emotion that includes Coping and Emotion Regulation

In this section, selected computational or mathematical models of emotion that includes coping and emotion regulation are reviewed. These models are EMA [Marsella and Gratch 2009], Bosse et al's Gross Model [Bosse et al. 2009] and Bracha and Brown affective decision making. [Bracha and Brown 2011]

2.2.1.1 EMA

One of the influential computational model of emotion that includes coping is EMA, Emotion and Adaptation [Gratch and Marsella 2004], [Marsella and Gratch 2009]. EMA implements the Lazarus appraisal theory and a coping system that indicates a way to handle an answer to an emotional state. In EMA, the agent has twelve appraisal variables that are used to give a signification of a situation from the point of view of the agent. EMA argues that certain inferences are minimally necessary to distinguish between different emotions. A computational model must represent events, actions, their consequences, future goals, expectation, causality, agency, relationships between people, other agent's mental state. EMA also emphasises on coping potential and coping strategies. EMA realizes this sets of requirements and assumptions.

EMA uses a representation built on the causal representations developed for decision-theoretic planning, augmented by the explicit representation of intentions and beliefs. This representation is a mixture of symbolic and numeric. Planning representations allow EMA to do causal reasoning and to calculate future outcomes. The decision-theoretic notions of probability and utility allow EMA to compute the appraisals of desirability and likelihood. Finally, explicit representations of intentions and beliefs are crucial to compute attributions of blame and responsibility and to model coping strategies, especially emotion-focused coping. .

Another key and unique aspect of EMA is that it integrates a model of coping with the appraisal process based on Lazarus's theory. Coping strategies work in the reverse direction of the appraisal that activates them, by identifying features of the causal interpretation that produced the appraisal that should be maintained or changed. Therefore, in EMA, coping strategies can be seen as control signals that manipulate the cognitive processes that operate on the causal interpretation.

There are four major types of coping in EMA: attention-related coping, belief-related coping, desire-related coping, and intention-related coping. To choose coping strategies, EMA uses a rule-based system. For example, EMA chooses problem-directed strategies if control is appraised as high, procrastination if changeability is high, and emotion-focus strategies if control and changeability are low.

2.2.1.2 A computational model based on Gross' emotion regulation theory [Bosse et al. 2009]

Bosse et al. [Bosse et al. 2019] proposed a computational model based on Gross' emotion regulation theory. The model is designed to be used for intelligent entities so the model is relatively lightweight and at high level where many aspects are addressed in an abstracted manner including the emotion itself and the consequences of different emotion regulation strategies. To illustrate, the main variables in the model are the level of emotion, the optimal level of emotion, slowness of adjustment, chosen emotional value, willingness to change emotion and cost of adjusting emotional value. Essentially, the model mainly concentrates on one specific type of emotion and did not model how the emotion arises. Instead, they model directly how different strategies changes emotion's intensity based on what Gross proposed.

The approach of the model is the Dynamical Systems Theory based on differential equations. The equations are used to define a mathematical relationship between each variable. The main equations are updating the emotion response level, updating the emotional values, and adaption of the modification factors. The model is evaluated in two ways: simulation study and verification based on Gross' finding using formal language, the Temporal Trace Language.

2.2.1.3 Affective Decision Making: A Theory of Optimism Bias [Bracha and Brown 2011]

Bracha and Brown propose a decision model with two cognitive process the rational and the emotional. The model is based on expected utility framework. The rational process maximizes the action (i.e., how much you want to buy insurance) while the emotional process maximizes the probability of good or bad events to happen. The processes share the same objective function except that, for the emotional process, there is another cost in the objective function which is the U-curve function representing a taste of accuracy to penalize the change of probability. This results in the competition between the two processes where one process drives another process further. For instance, when the rational process prescribes buying less than full insurance, the emotional process, in turn, leads the decision maker to believe "this is not going to happen to me" and to determine that she is at a lower risk. This causes further reduction on insurance.

3. Main Assumptions of the Model

A model is a set of assumptions. It defines the scope of the model, what include in the model and what do not. For this work, the set of assumptions connects decision and emotion together including appraisal theory, coping theory, and emotion regulation theory. To construct and derive a set of assumption, I start by looking from the perspective of Marr's 3 level analysis [Marr 1982].

3.1 Marr's 3 level Analysis

Marr's 3 level provides a way to understand any machine that carries out an information-processing. The three level are:

1. **Computational Level.** What does the system do? What problem does it solve?
2. **Algorithmic Level.** How does the system do what it does? What is the representation for the input and the output? What is the algorithm for the transformation?
3. **Implementation Level.** How is the system physically realised?

In this work, I only focus on the first two level and will not include the third level. The first level is the starting point of the model assumptions while the second level is the model description which is the topic of the section after.

3.2 Model's Assumptions

1. **Computational Level: Decision Problem.** *Given a situation and a set of available and aware actions, people choose the "best" action.*

The first assumption assumption has to do with the decision problem that people face which is how people decide which action to do from a set of aware and available action. The assumed answer to the problem is to pick the best action. The next step is to define what best means. Best implies that people subjectively *evaluate* the *consequences* of *actions*.

2. **Evaluation: Appraisal Theory.** *Consequences of action are evaluated based on beliefs, goals and other appraisal dimensions.*

We assume that how people evaluate the situation is based on the appraisal theory of emotion. This means we assume that people subjectively evaluate the current situation and outcomes of an action based on their goals and beliefs. In addition to the notion of goal, appraisal theories also provide us with additional sets of possible objectives that people may have including controllability and uncertainty.

3. **Consequence: The model of the world.** *To consider possible consequences of actions, people maintain a model of the world.*

This assumption is based on the idea of cognitive map [O'Keefe & Nadel 1979] and the idea of model-based reinforcement learning [Daw et al. 2005], which have many supports in the neuroscience literature that people maintain a model that used for planning for goal-driven behaviors. The model of the world is corresponded to one's beliefs about the world and oneself.

4. **Action: Coping and Emotion Regulation.** *The set of actions can be divided into two categories: 1) action that interact with the world directly, and 2) actions that interact with one's model of the world.*

The fourth assumption assumes that people can decide to act to change the situation and/or themselves. The assumption is based on the idea of problem-focused coping (changing environment) and emotion-focused coping (changing one's model of the world) from Lazarus' coping theory. Similarly, this assumption is also aligned with the notion of situation modification (changing situation), and reappraisal (changing one's model of the world) in the emotion regulation framework.

Two board emotion-focused coping strategies are the main focus of this work. The first strategy has to do with how people change the importance of some goals which can result in changing an intensity of emotional experience. We call any action that change the importance of goals, Adaptive Preference (AP) action. The second strategy has to do with how people change their beliefs about how the world is or how the world will be. We call any action that have to do with observation, Motivated Inference (MI) Action.

Figure 5 shows the diagram of the model's assumptions.

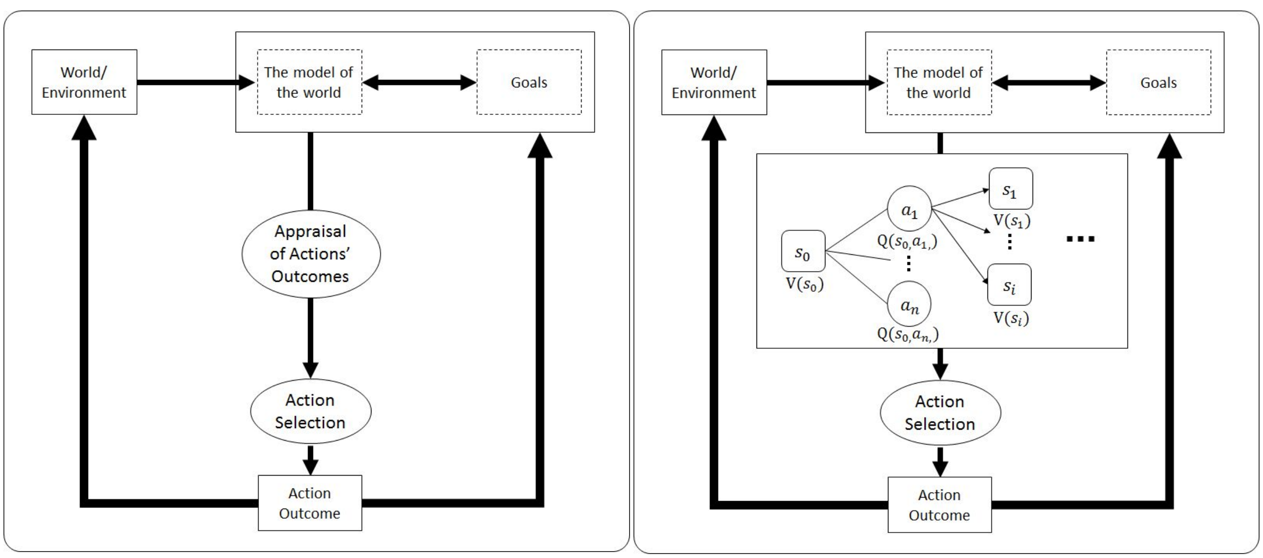

Figure 5: A diagram of the model's assumptions.

4. Model Description

In this section, we describe the model formally based on the set of assumptions above. The model can be divided into two parts: the representation and the algorithm.

4.1 The agent's model:

We model the agent's model as Markov Decision Process (MDP). MDP is a general sequential decision framework with few requirements and no constraints about human nature unlike existing cognitive architectures. It provides simple building blocks to guide the construction of the model for psychological theories that are descriptive in nature. MDP also comes with rich existing works that provide different algorithms with different characteristics to decide an optimal action given the model.

In the following section, we detail the five components of MDP, <S, A, T, R, γ >.

4.1.1 State (S):

A sufficient statistic of what occured in the past, such that what will occur in the future only depends on the current state, satisfying the Markov assumption. States are represented as a set or a vector of features. Features can be either numeric or categorical depending on the nature of features.

People may be uncertain about the world including the current state (Partially Observed), the transition probability and the importance of features (reward). To capture this, state's features including transition probability and reward weight are represented as a probabilistic distribution. As a result, these features will maintain sufficient statistics of probability distribution of transition function and reward function. The idea is based on Bayes Adaptive MDP (BAMDP) [Ross et al. 2011], [Guez et al. 2013].

4.1.2 Action (A) :

A set of actions (A) contains actions that people are aware of that they can do in a given situation. The main component of an action is the action's dynamic describe how the action changes the features in the current state. Follow from the assumption about actions and the above definition of actions, this implies that actions can change any features in the state including features describing the current state and features describing the knowledge about the current situation.

Describing the dynamic or consequence of actions is the job of the modeller and is also assumptions that the modeller makes for a given situation or task. Different people could have different beliefs about the dynamic of actions. In addition, different people could aware of different sets of action for a given situation. A careful treatment of individual difference on actions is beyond the scope of this work. To work around this issue, the proposed experiments for evaluation will have a same set of straightforward actions for every participants.

The dynamic of actions that change either transition probability (beliefs) or the reward function (goals) is the main focus of this work and require careful treatment. The main dynamic that need to be define for these actions are their cost which will constraint how much one can change their beliefs or goals without any additional observation.The following list contains different ways that I will explore how to model the cost of these actions.

- The cost is proportional to the variance of the original distribution. This means that as we certain about the consequence of action or the important of goal, it makes it harder to change the beliefs about them.
- The distance between the two distribution (original vs target). The more difference, the harder to change. The measure of difference between two probability distributions is KL-divergence.
- U-shape function as in Bracha and Brown 2011.
- A fixed cost value depending on the type of beliefs and goals.

4.1.3 Transition Function (T):

Transition Function (T: P(s'|s, a)) describes a probability of being at a state s', from state s and executing an action a. Transition function is calculated based on the current value of the corresponding features of sufficient statistics in the state s. Transition function can also be defined at the state's feature level where we assume that each feature is independent.

4.1.4 Reward Function (R):

Reward Function (R : S , A - > $\Re$) is a function that map a state and an action to real number. Specifically, we define the reward function as a vector of weights for each goal reflecting important of each goal. Current status of goals are based on the features in the state. The weights themselves are a probabilistic distribution. As it stands, reward function in MDP can be viewed as appraisal process that translates a given state representation of a situation to a singular value representing emotional significance of a situation.

The reward function is assumed to be a standard linear weighted sum of each feature. This assumption has an important implication which is different goals can be converted into the number on the same scale and can be summed together.

According to appraisal theories, two additional objectives are included in the reward functions: controllability and uncertainty. Un/certainty is based on variance of the distributions of transition probability of features. Controllability or coping potential is based on expected reward of available actions with higher reward than current state. These formulas are another exploration point in this work.

In addition, states and goals are tightly connected where one can help identify the other. For instance, we may have some initial ideas about what goals are salient in the given situation. These goals can help identify what features a state will have. For example, in the event of hurricanes, one of the main concern is about the flood condition so the state should contain information about flooding. On the other hand, given the context, we may know some features of states which in turn will help us identify related goals. For example, in a game, we may know and maintain the status of enemies in the state and this can tell us that the status of enemies can be a goal.

Similar to action, defining a set of goals for a given situation is the job of the modeller. Crowdsourcing could be used to help identify goals for a given situation. However, goals can be either explicit or implicit which means that people may have goals that do not fully aware and cannot report them. A complete model of goal and goal structure is beyond the scope of this work. Omission of goals may cause the model to perform worse. However, I expect that with well-defined states and survey questions should allow to identify majority of significant goals for most people.

4.1.5 Discount Factor (γ):

Discount Factor ($\gamma \in [0,1]$) is a factor that discounted the reward of future situation or outcome, where t is a time step in the future. This reflects that future rewards are value less than the current reward. Discounted factor can also be viewed as reflecting uncertainty in the future. Discounted factor allows the model to capture the different in intertemporal choice and impulse vs control issue. Two forms of discount factor will be considered in this work, exponential and hyperbolic.

4.2 Algorithm

In this section, I detail how the agent can use the model to make a decision.

4.2.1 Action Selection and Planning

In MDP which is a sequential decision framework, an agent chooses an action that is the best in terms of cumulative reward picking an optimal action not just in the present but also in the future. This is the optimality principle which leads us to the following equation, called Bellman's equation [Sutton and Barto 2018].

$$v_*(s) = max_a\, E[R_{t+1} + \gamma v_*(S_{t+1})|\, S_t = s, A_t = a] \quad (1)$$

$$= max_a \sum_{s',r} p(s',r|s,a)[r + \gamma v_*(s')] \quad (2)$$

$$q_*(s,a) = E[R_{t+1} + \gamma max_{a'} q_*(S_{t+1},a')|\, S_t = s, A_t = a] \quad (3)$$

$$= \sum_{s',r} p(s',r|s,a)[r + \gamma max_{a'} q_*(s',a')] \quad (4)$$

$v_*(s)$ is an optimal value (cumulative reward) of the state and $q_*(s,a)$ is the optimal action value of the state and action pairs. In this work, we explore two ways of solving MDP: Dynamic Programming Based Method and Sampling Based Method.

4.2.1.1 Dynamic Programming Algorithm

This dynamic algorithm for solving MDP is called Value Iteration (VI) and it simply follow from equation (2). The following equation describes the recursive relationship for a simple update of v ,

$$v_{t+1}(s) = max_a \sum_{s',r} p(s',r|s,a)[r + \gamma v_t(s')] \quad (5)$$

, where t is a time step. This is an exact method and run-time grows exponentially based on the branching factor and the depth of the future. Therefore, this method can only be applied in small examples. Still, many human decision situations do not involve many actions and future steps unless we take into account the future beyond a given situation. The depth of the search can be thought as the limitation of resource.

4.2.1.2 Sampling Based Algorithm

Another to calculate expectation for v or q value is by using empirical expectation calculated based on samples drawn from the model. From equation (1) and (3), the v and q value are the expected cumulative future discounted reward starting from a given state. One direct way to estimate it from samples of trajectories (or experience), is to average the returns of many samples of trajectories starting at that state. The average should converge to the expected value as more samples are observed. The model only need to generate or simulate sample transitions and not the complete probability distributions of all possible transitions unlike VI. We call this type of method, Monte Carlo Method.

One particular sampling based algorithm that we will consider in this work is Monte Carlo Tree Search (MCTS). MCTS is a recent and very successful algorithm {\cite alpha go, RLbook}. MCTS does not calculate action values for every states but only compute estimates of action values for a given current state and for a given policy called the rollout or search policy which determined the actions in the simulated trajectories. Therefore, MCTS is executed after encountering each new state to select the action for that state; it is executed again to select the action for the next state, and so on. The core idea of MCTS is to successively focus multiple simulations starting at the current state by extending the initial portions of trajectories that have received high evaluation from earlier simulations. The estimated values are maintained only for the subset of state-action paris which from a tree rooted at the current state. MCTS incrementally extends the tree by adding nodes representing states that look promising based on the results of the simulated trajectories.

MCTS consists of four steps in the loops until no time is left as followed.

1. Selection: Starting at the root node, a policy based on the action values on the edges of the tree traverses the tree to select a leaf node.

2. Expansion: On some iteration, the tree is expanded from the select leaf node by adding one or more child nodes reached from the selected node via unexplored actions.

3. Simulation: From the selected node, or from one of its newly-added child nodes, simulation of a complete episode is run with actions chosen by the search policy.

4. Backup: The return value generated by the simulated episode is backed up to update the action values on the edges of the tree traversed by the policy in this iteration of MCTS. For states and actions visited by policy beyond the tree. values are not saved.

Recent works {\cites} have raised the benefit of sampling based method for modelling human decision. Specifically, Leiden et al 2018. have shown that, in the context of expected utility, using importance sampling generate samples from a distribution based utility of outcomes can explain many existing phenomenons in decision-making. They derive this method based on the idea that the number of samples can be thought as a constraint related to resource for making decision. Therefore, as decision-time method, it has limit amount of samples that can be drawn and may not be able to get good representative samples by drawing directly from the distribution. By drawing from an utility based distribution, it yields finite samples that minimize bias and variance unlike drawing directly from the distribution that yield unbiased estimate but variance can be large. In this work, we will explore how to extend importance sampling to MDP via sampling policy for MC methods.

4.3 Limitations

Emotion and decision-making connect to many topics beyond the topics included in this work. This section details some important topics that do not get included in the proposed model. This list does not mean to be exhaustive. Some limitations have already been mentioned above such as issue about defining actions and goals. Identifying things that are not included in the model should help provide a clearer scope of the model itself. At the same time, this section also serves as future work section.

The list of some important topics and limitation is as follows: attention, body, social element, conscious vs unconscious, memory, learning, full treatment of time dynamic and many more. Below we give some details for the first four topics.

The first important element that is not included in the proposed model is attention. Attention is one of the main component in the process model of emotion regulation and also is in some of appraisal theories such as OCC. The model does capture some notion of attention implicitly in term of the weights of goals can guide how people do look ahead. In this sense, one can look at weights of goals as the level of salient that pull people to think more and pay attention on some outcomes. However, the proposed model does not include an explicit way to model attention and the action of shifting attention and the cost of its. The full treatment of attention is left for the future work.

Another excluded element is body and interoception. We exclude body in this work does not mean that the model could not deal with body change. For example, features in the state can include heart rate, sugar level, level of hormones or abstract energy's level. The issue with modelling body is that it requires careful treatment of the dynamic of body and the connection between physiological state and goals. To the best of my knowledge, many things about our body are still mysterious.

The next excluded element is social aspect. This includes theory of mind, verbal and nonverbal communication, some form of agency, and causal attribution which allow for identifying persons who causes the situation and calculating blameworthiness of oneself and other people. These mean to include social aspect the model requires a component for theory of mind and causal attribution. We left this for the future work.

The last exclusion is consciousness. We do not make any assumption about conscious and unconscious in the current model. In this work, we follow Marr three level of analysis and focus on the first two levels, computational level and algorithmic level respectively. At the computational level, we define what the problem that system solves which is the first assumption on choosing the best action. At the algorithmic level, we define how the system solves the problem which is the proposed model. Putting it this way, the proposed model does not need to capture the notion of consciousness to solve the problem. At the same time, we still lacks an understanding of consciousness, especially in term of the purpose of consciousness. Still the issue of consciousness can influence the current work because any unconscious experience cannot be reported by subjects. A careful treatment of consciousness for the model is an important future work.

Although we did not include these in our current model, this does not mean there is no existing work on this topic and emotion. For example, ACT-R phi {\cite} has tried to link the body model to the cognitive architecture. Thespian {\cite} has a social element that include computation for blameworthiness and causal attribution.

5 Evaluation: Simulation Study

In this section, we demonstrate the model via a simulation studies of the two main coping strategies: changing beliefs and changing goals. The main purpose of these simulation studies is to demonstrate that, given the model, it is possible to observe the phenomenon under reasonable value of parameters. The two simulations are an adaptive preference example which is Fox and Sour Grape story, and a motivated inference example which is a mother and a guilty son story.

5.1 Adaptive Preference: Fox and Sour Grapes

Fox and Sour grapes is the Aesop's fable that commonly use to demonstrate an adaptive preference. In this story, a hungry fox tried to reach some grapes hanging high on the vine but was unable to, although he leaded with all his strength. After a few tries, a fox decides that grapes are sour and does not want to eat it anymore. A fox walks away to find something else to eat instead.

As a story shows the fox changes his preference on grapes from good to bad. This story is a good example to demonstrate adaptive preference for the model because the fox cannot really do anything with observation which in this case whether it successfully jumps to get grapes or not. Figure 6 shows the setup of the model for the story.

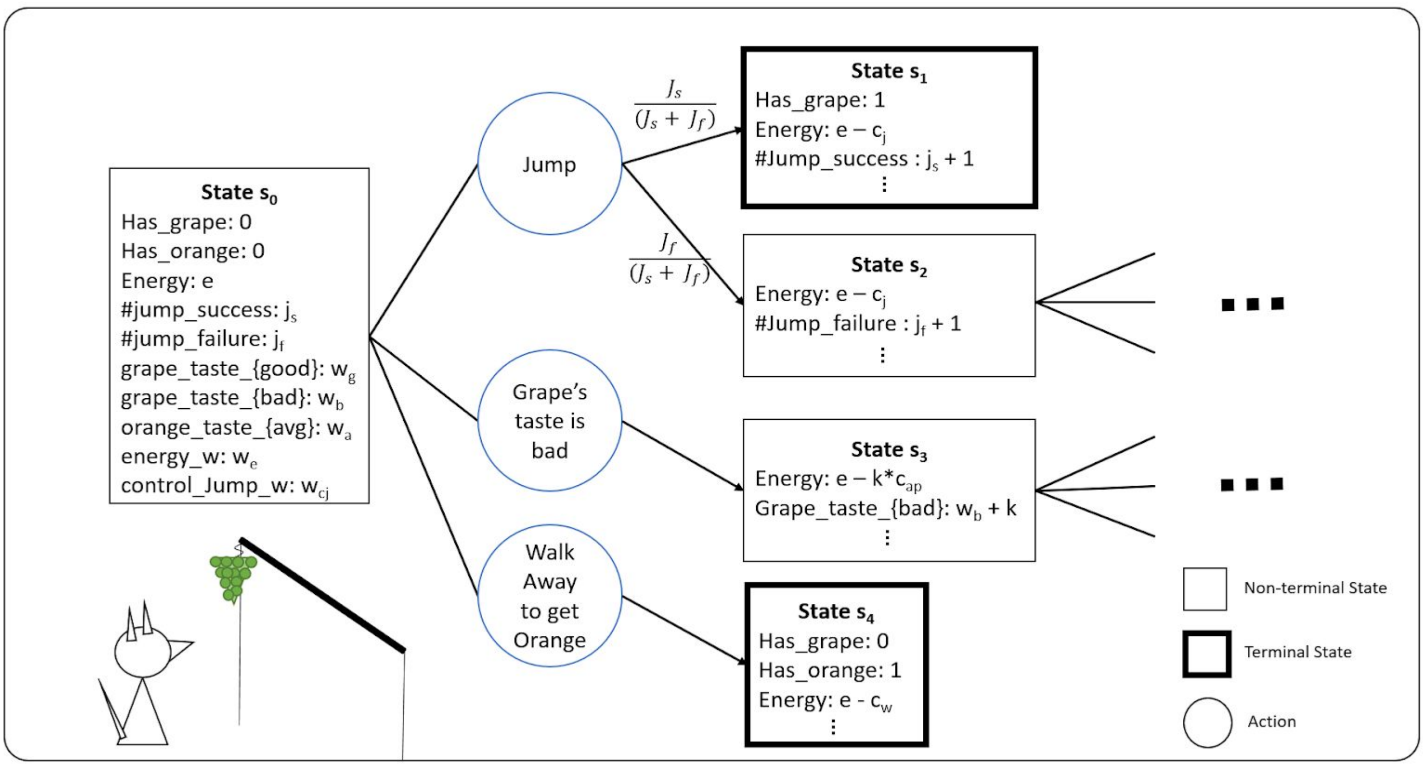

Figure 6: A model of fox and sour grape. The equation on jump's edges are the probability of being at that connected state.

The state's feature include energy level, has grape, has orange, jump success, jump failure, grape taste good, grape taste bad, orange taste average, importance of energy, jump's control weight. The first three features are features representing the state of the world while the rest represents the current model. There are two physical actions in this situation: jump or walk away to get orange. Jump success and jump failure maintains the count of success and failure. The probability of successful jump is calculated based on jump success/(jump success + jump failure). Any other things are assumed to only have one outcome such as the taste of orange and importance of energy. For adaptive preference action, we only model the action that reduce the taste of grape. This is achieved by adding the count to grape taste bad. The cost of adaptive preference is proportional to the number of count added into the grade taste bad.

In the simulation, we will investigate different combination of parameters in the model. These includes the distribution of weights of rewards (grape and energy), the distribution of transition function (mainly jump), the true ability (the true probability of successful jump), the cost of actions (both AP and jump), the utility of taste (good, bad, and average), and the constraint on the resource for thinking. We expect to see that under some reasonable parameters' value, a fox will decide to adapt its preference, demonstrating that AP is the subjectively best action.

6. Evaluation: Empirical Data on Human Decision During Hurricane

The second evaluation is based on empirical data from human decision during hurricanes. Hurricane is an important domain because it involves life-threatening situation. Hurricanes is one of the most devastating natural disasters and 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. In 2017, Hurricane Harvey, the costliest tropical storm on record, made landfall at Texas, caused an unprecedented flooding resulting in hundreds of thousand of inundated houses, at least 107 deaths, and a total damage of $125 Billion. Hurricane Irma made landfall at Florida caused at least 138 deaths and at least $65 Billion of damage. Two weeks after Irma, Hurricane Maria struck Puerto Rico and caused $91 Billion of damage, at least three thousand death, and became the deadliest Atlantic Hurricane.

6.1 Background on Hurricane

There are three characteristics of a hurricane that are critical to this work. The first characteristic is the impact of a hurricane. A hurricane can cause a large waves, heavy rain, floods, and strong wind which can damage or destroy objects and building along its path, potentially leading to utility outages. The second is the time between the first notice and the landfall. This duration can last a few days.

For example, Hurricane Harvey formed on August 17 and made landfall on August 25. Hurricane Florence formed on August 31 and made landfall on September 14. Hurricane Michael formed on October 7 and made landfall on October 10. The third characteristic is high uncertainty. Currently, hurricane track can be predicted quite accurately, but the intensity and the impact of the storm still cannot be predicted well. [Roger et al. 2013]

From the perspective of human evacuation behavior, there has been much existing research [Dow & Cutter 2000], [Lindell et al. 2005], [Dash & Gladwin 2007], [Hasan et al. 2010], [Huang et al. 2016]. These studies mainly focus on identifying features ranging from demographic information, communication, and risk perception 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. 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 including mixed logit model and repeated logistic regression. [Gladwin et al. 2001], [Pel et al. 2012], [Murray-Tuite & Wolshon (2013)], [Yin et al. 2014], [Xu et al. 2016]. The limitation of some of these models is the lack of the ability to explain the decision. Another limitation across these models is that they only consider the current condition, but not the predicted conditions from future information.

6.2 Hurricane Situation Break Down

From the perspective of the model, there are two main components for the decision model during the hurricane events. The first one is the person. Based on the proposed model, we can further characterize the person into goals (appraisal dimensions) and the model of the world. For goals, these include safety, money, living conditions, and uncertainty of Information. For model of the world, it includes prior beliefs about hurricane, features related to goals and other demographic characteristics that are not related to their goals. We cannot manipulate easily characteristics of a person. This means we have to ask the person to measure them.

The second component is the situation, especially the impact of the hurricane. In the case of the hurricane event, the situation of hurricane comes from information that the people receives because they do not observe the hurricane directly. Unlike person, it is possible manipulate or create information so it is the main variable for control experiments for the control experiments.

6.3 Evaluation

As hurricane is a complicated situation, we break down the evaluation into three parts with three different experiment conditions. The first evaluation aims at appraisal theory as the evaluation function or reward function, specifically goals and their weight. To do so, we collected questionnaire data from states affected by two 2018 major hurricanes: Florence and Michael. The questionnaire data is suitable for identifying the real goals or concerns that people may have during the hurricane and to evaluate how well these concerns can be used to predict the actual decision. The next section covers this evaluation.

The second evaluation is on coping strategies, change of beliefs and changes of goals. In this evaluation, the aim is to investigate the nature of these coping strategies and evaluate different ways of model them, specifically the cost of these two actions. However, questionnaire data cannot be used for this part because we want to observe changes in beliefs and goals and that requires to ask the same person multiple times which is hardly feasible in the real hurricane event. Therefore, in the second evaluation, we need to create control experiments manipulating a set of information and measuring changes in beliefs and goals after each set of information. The 8th section covers the control experiments to collect the data for this evaluation.

The third and last evaluation is on sequential nature of the decision-making during the hurricane. In this evaluation, we would like to evaluate the importance of taking into account the sequential aspect of the event, specifically future information gain, in predicting the decision. Similar to the second evaluation, we cannot evaluate this aspect of the model using questionnaire data and have to rely on data from the control experiments.The 8th section covers the control experiments to collect the data for this evaluation.

7. Preliminary Work: Hurricane Questionnaire

The preliminary work focuses on evaluation of two things: 1) important goals (appraisal dimension) that people consider during the hurricane and 2) evaluation of the prediction of the decision based on using these goals to calculate reward value of two actions - evacuation and stay. Three major concerns are identified based on the characteristic of impact of hurricane and from literature. These three concerns are safety, money, and experience. Two experiences that we focus on are flooded condition and electricity condition. We collected questionnaires from two 2018 major hurricanes: Florence and Michael for this evaluation.

7.1 The Model

Because of the nature of questionnaire data, the preliminary work focused on one step decision-making. As a result, we simplified MDP into expected utility calculation based on reward function. Expected utility calculation can be transformed into logistic regression to predict a probability of choosing actions. To fit the data, I use Hierarchical Bayesian Logistic Regression (HBLR) implemented in Stan [Carpenter et al. 2018]. HBLR allows for effectively estimate the potential group difference in the weights of features (rewards). This allows us to get closer to capture the individual difference regarding importance of goals. However, since we only have one measurement per participants, we cannot estimate parameters for each participants and have to group participants based on different features and estimate group-based parameters instead.

In addition, I built a simulation of a full sequential model that consider not only concerns and risk perception, but also future information. The simulation is used to investigate the impact of future information. However, the questionnaire data could not be used to validate the simulation. The reason is that we need a sequence of beliefs measurement as participants received new information but we only asked participants once resulting in only one measurement per participant.

The consideration of future information is an important aspect because the unfolding of a hurricane event, from formation to landfall, can span days. People who stay repeatedly face the evacuation decision as they receive new information. Further, there is a high degree of uncertainty concerning the path and intensity of hurricane. Thus decision-making during a hurricane is sequential and people may consider not only current condition but also future information that could help reduce the uncertainty.

Information is model directly as a transition features maintaining the current knowledge of the world as described above. Representing the transition functions explicitly allows the model to do look ahead and consider what an agent can do better when observing new information. In this way, the value of information is equal to the utility gain from making better decision given that information.

One important assumption about the information during the hurricane that we make is that the news (information) about hurricane from today (current time step) is much better and more accurate than the news (information) from yesterday (previous time step). As the information becomes more certain, it will eventually dominate the prior belief. As the uncertainty goes down, the probability of one outcome will keep going up and get closer to one.

Figure 7 shows an instantiation of the model for the hurricane decision.

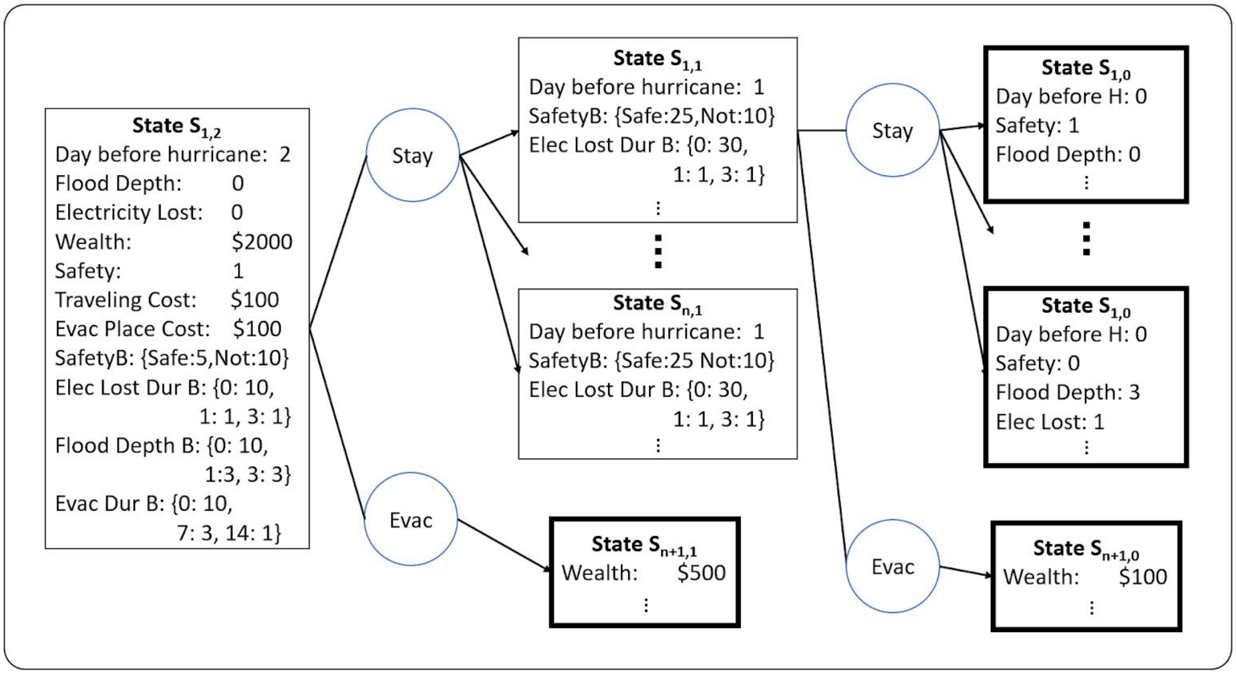

Figure 7: an instantiation of the decision-making model in the events of hurricane. A square represents a state which contains a list of features and their value. The bold border represents terminal state while the non-bold border is non-terminal state. The circle represents action which consists of either stay or evac.

7.2 Questionnaire Design

In addition to standard questions including demographic information, previous experience and official notice, the questionnaire also includes questions about the parameters in the models. There are two types of parameters so there are two types of questions: transition-related questions and goal-related or utility-related questions.

For transition-related questions, we either ask participants what they think will happen or how likely it is that certain events will happen. Example of some questions are: How high (in feet) did you expect your house to be flooded? How long did you expect for your area to lose electricity after the hurricane hit? How long did you expect it to take for your area to return to the normal conditions after the hurricane hit? What do you expect it would cost, in dollars, to travel to a safer place? How likely that the hurricane would pose a serious threat to your safety if you stay in your home during the hurricane? We use seven step likelihood scale for probabilistic questions and not free response since participants were unlikely to be able to provide precise probabilistic estimates.

For utility-related questions, the main concern is on the utility associated with specific experiences. In other words, we would like to know how good or how bad a certain experience is from a participants' perspective. In order to measure this utility, we opt to ask participants how much would you pay not to experience a certain event such as living in a flooded house or without electricity. For example, assume your home became flooded with 3 feet of water for 5 days, how much would you be willing to spend (in dollars) to stay in a hotel for those days instead of your home? The question is also a free response question so that we would not bias participants answer that some values are high or low. Note that we did not ask participants for money equivalent of not being seriously injured, because we believe that it would be hard for participants to answer it meaningfully. Instead, we opted to estimate the cost of not being in seriously injured (safety cost) from data along with a noise cost. These results in a model with only two parameters $SafetyCost$ and noise term.

7.3 Data Collection

To collect the data, we used Amazon Mechanical Turk (MTurk) service to send out questionnaires to participants in the states that affected by the hurricane. We collected data from two recent hurricanes: Florence and Michael. Hurricane Florence made landfall on September 14 affecting South Carolina and North Carolina. We sent out a pre-questionnaire on September 10 and stopped collecting on September 11 obtaining 404 responses from SC and NC. Then we sent out a post-questionnaire on September 21 and stopped collecting on September 29 obtaining 747 responses from SC and NC. Hurricane Michael started forming on October 7, became a hurricane on October 8, and made landfall on October 10 affecting Florida and Georgia. Due to the brief period between forming and making landfall, we did not send out a pre-questionnaire. We sent out post version on October 18 and stopped collecting on October 22 obtaining 700 responses from FL and GA.

7.4 Results

We evaluate the model in two ways: quantitatively using questionnaire data collected from previous work, and qualitatively using simulation. We use this data to evaluate key decision-making assumptions of the model, specifically appraisal dimensions as an evaluation function, and to evaluate the predictive ability of the model within each dataset and using one hurricane data to predict the other.

For qualitative evaluation, we simulated different types of hurricane scenarios across different demographics to evaluate the model's prediction on sequential decisions. We also compare the prediction between model variations that consider future information versus ones that do not.

7.4.1 Empirical Results

Table 1: Mean ($\bar{x}$) and 95% CI of the weight of all model-related features for both datasets.

Features	Florence		Michael	
	$\bar{x}$	95% CI	$\bar{x}$	95% CI
Safety	-5.0	[-6.6,-3.5]	-4.1	[-5.6, -2.7]
Flood Cond.	0.7	[0.5,1.0]	1.0	[0.7, 1.4]
Elec Cond.	0.3	[0.0, 0.5]	0.7	[0.3, 1.1]
Travel Cost	-0.3	[-0.6, -0.1]	-0.4	[-0.7,-0.1]
Place Cost	-1.1	[-1.4,-0.8]	-1.3	[-1.7, -0.9]

Table 2: The LOOCV accuracy (ACC) and F1-score (F1) for each different sets of features for both datasets.

Feature sets	Florence		Michael	
	Acc	F1	Acc	F1
Intercept only	84.80%	0.00	80.81%	0.00
Demographic	87.13%	0.46	81.37%	0.28
Demo + Others	90.79%	0.65	89.11%	0.70
Model-Related	91.52%	0.67	89.95%	0.70
Hierarchical	**94.44%**	**0.80**	**92.80%**	**0.80**

Table 3: The accuracy and F1-score of each set of features using one dataset to train to predict the other. M = Michael and F = Florence

Feature sets	M to F		F to M	
	Acc	F1	Acc	F1
Demographic	85.82%	0.20	74.54%	0.35
Demo + Others	89.04%	0.63	85.61%	0.62
Model-Related	90.64%	0.7	88.93%	0.63
Hierarchical	**93.42%**	**0.80**	**92.62%**	**0.80**

Table 1 - 3 show the results of empirical validation. Table 1 shows the mean and 95\% credible interval (CI) of model-related features for both Florence and Michael data. Flood total and evacuated place cost total are the result of each value multiplied with the duration. All features are normalized and both cost features got log-transformed first. From table 1, for both datasets, 95% CI of all weights of the features do not include 0 and the sign of all weights are in the expected direction. Safety probability, traveling cost, and evacuated place cost are negatively associated with evacuation decision while flood condition and electricity condition are positively associated with evacuation decision.

Table 2 shows the accuracy and F1 score of different sets of features for each data calculated from Leave One Out Cross-Validation (LOOCV) using loo package. [Vehtari et al. 2017] The results show that using only features from the models outperforms other sets of features not including them in both measurements for both datasets. The full hierarchical model outperforms all other models and achieves relatively high accuracy and F1-score for both datasets.

Table 3 shows the accuracy and F1 score of different sets of features trained using one dataset to predict the other. Similar to within dataset results, using only model-related features outperforms other sets of features not including them and the full hierarchical model outperforms all other models achieving relatively high accuracy and F1-score for both datasets.

7.4.2 Simulation Study and Results

In this section, we detail the simulation study to evaluate the model. There are two purposes of the simulation. First is to test the effect of different factors that can influence the decision in the model, specifically whether they are in the expected direction or not. These factors include the prior distribution, the reward weights, information and the dynamics of information. The second is to demonstrate the effect of future information by comparing the differences between the model with and without lookahead to consider future information.

In this simulation study, a state includes the following features: 1) flood depth with five possible outcomes either 0, 1, 3, 5, or 7 feet, 2) flood duration with five outcomes either 0, 3, 7, 14 or 28 days, 3) electricity lost duration with five outcomes either 0, 1, 3, 7, or 14 days, 4) safety with two outcomes either safe or not safe, 5) traveling cost, and 6) evacuated place cost. The four features have corresponding information features (distributions over their 5 categories) while both costs (5 and 6) only have one fixed value at each time step (and therefore no associated distribution). The evacuation duration is the same as flood duration. One-time step is equal to one day and the simulation starts 5 days before the hurricane hits.

For five-category information features, we simulate only three possible type of future information - the first ("A" = All right), the third ("B" = Bad), and the fifth ("C" = Catastrophic) in order of magnitude. For two-category information feature, we simulate on both categories where safe is labeled "A" and the not safe is labeled "B".

Aside from different sets of information, we test the following three factors. First is the dynamics of information. Two dynamics of information that we test are the low rate of reduction and the high rate of reduction. The qualitative expectation is that, in the low rate case, prior distribution will have more influence.

Another factor is the prior distribution of information features. We test two types of initial distributions of information features: good prior where low impact outcomes have high probability and bad prior where high impact outcomes have high probability. The qualitative expectation is that different priors should result in different evacuation probability at an early time step before information dominates.

The last factor is the different sets of reward. We test three types of reward: high weight on money, high weight on safety, and the reference reward with relatively low weights on both money and safety. The qualitative expectation is that a high weight on money should result in increased likelihood to stay while a high weight on safety should result in increased likelihood to evacuate.

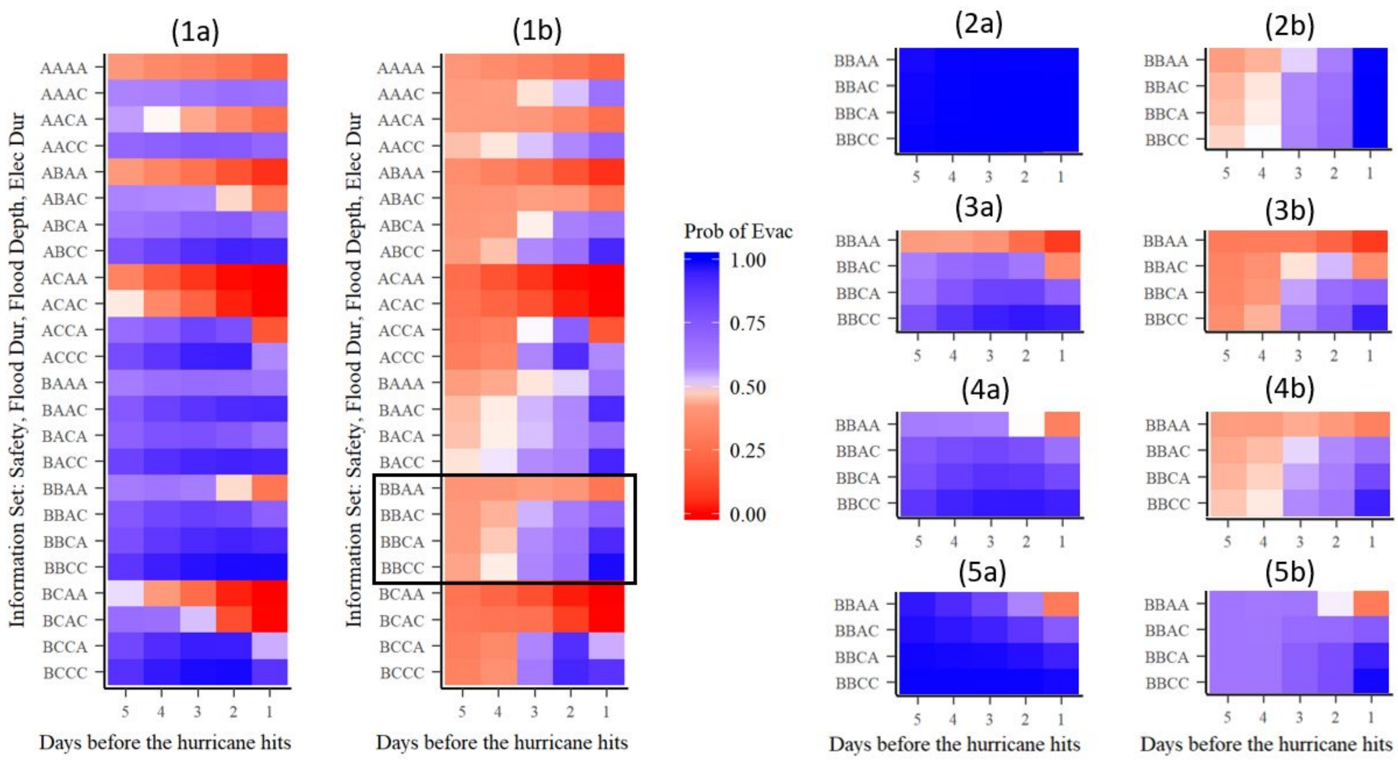

Figure 8: The simulation results. Y-axis is a set of information. (a) is without lookahead and (b) is with lookahead. (1) is reference scenario. (2) has higher safety reward's weight (3) higher money reward's weight (4) has lower rate of reduction. (5) has bad prior.

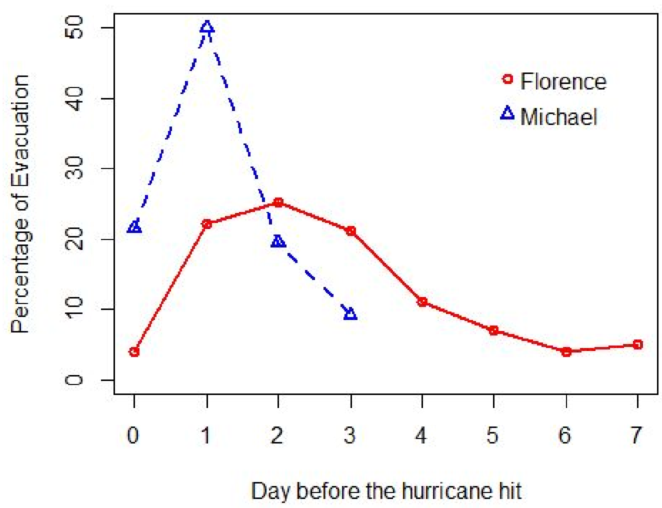

Figure 9: Distribution of when people evacuated from our survey

Figure 8 shows the results of simulations. The x-axis is the time step in day. The y-axis is alternative information set where each set is characterized in term of 4-tuple: <safety, flood duration, flood depth, electricity lost duration>. (a) is the model without lookahead. (b) is the model with lookahead. (1) is the model with reference reward, good prior, and high rate of reduction of uncertainty. With (1) as a reference point, (2) has higher safety reward's weight. (3)

has higher money reward's weight. (4) has a low rate of reduction. (5) starts with bad prior. The box at (1b) highlights the same set of information across (2) to (5). The probability of evacuation is calculated using a softmax function between the cumulative value of stay and evacuate.

Across different conditions, we see that P(evac) without lookahead is greater than the P(evac) with lookahead, especially on earlier time. At the last day, both models yield the same probability since there is no more information to look for. Figure 9 shows the distribution of the day that people evacuated for hurricane Florence and hurricane Michael. From the figure, people who evacuated did not evacuate immediately after knowing about the hurricane and more people evacuated at the time closer to the day the hurricane hit than earlier. The model without lookahead seems to overestimate the P(evac) of subjects in these two hurricane compare to the model with lookahead.

With these results, we now focus on the model with lookahead. Figure (1b) shows the results across multiple information sets. If we look at the set of information with the same flood duration, we see that as the sets of information go from bad to worse, P(evac) increases. We do not observe this as flood duration increases because flood duration influences both outcomes of stay and evacuation.

We now turn to the results of different conditions using (1b) as a reference across a few different information sets. In (2b), the reward has higher safety weight and we observe P(evac) in (2b) to be greater than (1b). In (3b), the reward has higher money weight and we see P(evac) in (3b) to be less than (1b). In (4b), the reduction rate of uncertainty is lower and we see that overall P(evac) still follows the same trend but slightly less due to good prior. In (5b), the prior information features are bad, and we see that P(evac) at an earlier time step is greater, but getting closer as the time step increases. Altogether, we see that the simulation results of the model with lookahead are in the expected direction.

7.5 Discussion

The results from actual hurricane questionnaire data show that the model-based or appraisal-dimension features are significant predictors across the two datasets. Using these features together with group-based weights achieves relatively high accuracy and outperforms other sets of features both within the dataset and even across the datasets. These results demonstrate our model's quantitative predictive ability and validate how well appraisal dimensions, specially goals and beliefs, can be used to approximate how people evaluate different outcomes. In addition, the results also suggests that the reward function is a good approximation.

Furthermore, we show that across different simulation scenarios our model predicts human sequential decision in the expected direction. In addition, the model with lookahead yields predictions closer to real hurricanes than the model without lookahead. Together, these demonstrate our model ability to qualitatively predict human sequential decision and the importance of information.

8. Proposed Evaluation: Control Experiment on Hurricane Decision

The main limitation of the questionnaire data is the feasibility of measuring the change of beliefs and goals as people received new information which is what we need to evaluate the remaining parts of the model. Therefore, it is necessary to conduct control experiments that would allow us to manipulate the information that people receive and measure beliefs and goals after each set of information.

8.1 Experiment Hypothesis and Evaluation

The proposed control experiments aim to collect the data to validate the following qualitative prediction:

Hypothesis 1: People change their beliefs on the impact of hurricane in the direction that make their prior choice favor or better based on appraisal and constrained by the distribution of those beliefs

Hypothesis 2: People change importance of goals in the direction that make their prior choice favor or better based on appraisal and constrained by the characteristic of the goals.

Hypothesis 3: People take into account the future information.

In addition, the data from the experiments will be used to evaluate the quantitative aspect of the above three hypothesis. Specifically, the data will be used to evaluate the accuracy of different ways of defining the cost of actions of changing beliefs and goals, and to evaluate the improvement of taking into account the changes of beliefs and goals will lead to improvement in prediction of the decision.

8.2 Experiment Condition

The main independent variable that we will be manipulated is the information about hurricane which can be will as the situation itself. This is because we cannot observe the hurricane directly and have to infer it from the available information. There are four characteristics of information that we will be manipulated to evaluate the model. The first one is the type of outcomes, specifically, the impact of hurricane which includes safety, flood condition, electricity condition, traffic jams, safe place cost, order or suggestion, and source of information.

The second characteristic is the parameters of each outcomes which includes value, likelihood or probability, and the uncertainty of the likelihood or probability. These three parameters derive directly from the representation of the feature which is dirichlet distribution where the value and probability come from the category with the highest count. The uncertainty of the likelihood or probability can come from either the information itself or the number of information that says the same things.

The third characteristic is the sequence of information. This includes the number of time step or the number day and the time interval between each step or day. For example, one condition is non-sequential which means there is one day. The other two consist of three days but one is 3, 2, and 1 days before the hurricane and the other one is 5, 3, and 1 days before the hurricane. The sequence of information also include the dynamic of the intensity of the hurricane. There are five dynamic conditions: the intensity is increasing, decreasing, as predicted from the beginning, increasing then decreasing, and decreasing then increasing.

The fourth and last characteristic is the realistic of the information. There are three conditions ranging from less to more realistic: text only, text with image, and video (with subtitle).

8.3 Experiment Details

The flow of the experiment is as followed.

1. Entry questionnaires on demographic information, previous experience, and prior knowledges and concerns about the hurricane
2. The main experiment.
    - 2.1. Each trial consists of a few number of consecutive decision points (day in hurricane) and a set of information depending on the condition
    - 2.2. Along side the set of information, they will be presented with two choices: evacuate or stay.
        - If choose stay, participant will allow to choose to stay or evacuate on the next day.
        - If choose evac, participant will not allow to make another decision but still allow to view information
    - 2.3. After making decisions, participants will be asked to report their current beliefs about the outcome of the hurricane.
3. At the end of experiment, participants will be asked about their experiences on the experiments.

Figure 12 shows a current version of the experiment.

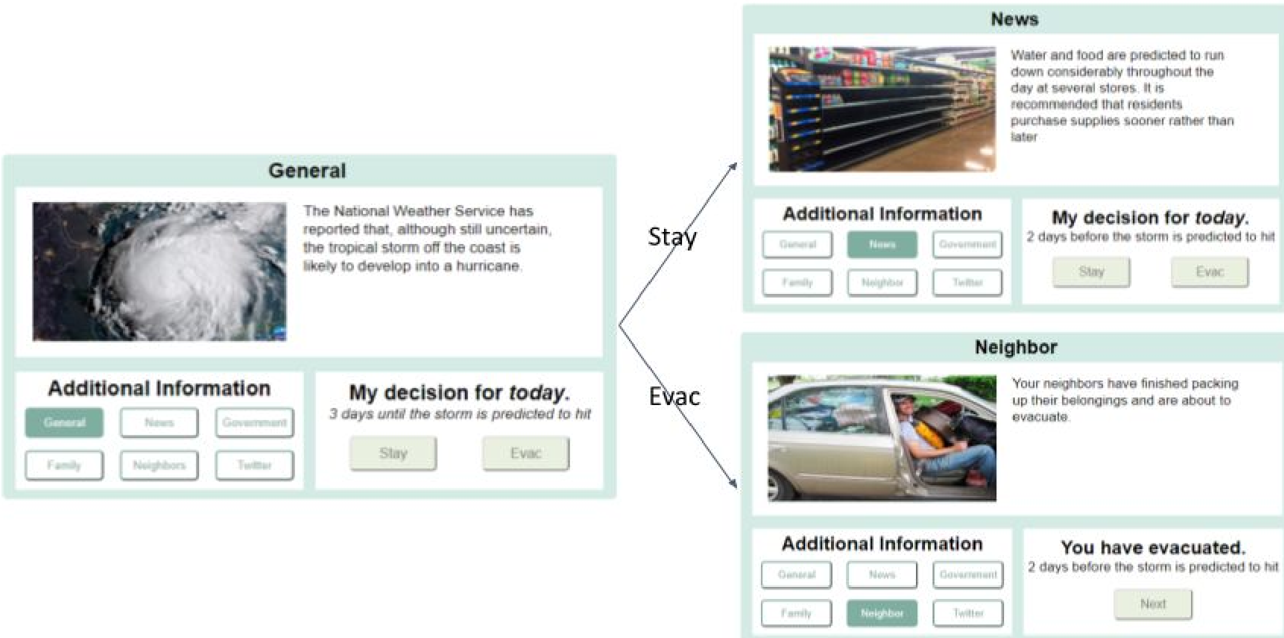

Figure 12: a control experiment for hurricane decision. The left figure shows the interface of the experiment. The top portion shows the detail of information. This could be either text alone, text with image or video depending on the condition. On the bottom left of the interface, this is the information selection area where participants can choose to see different information. On the bottom right of the interface, this is the decision area where the available choices are presented for participants to choose. If participants choose stay, they can choose to stay or evacuate in the next day as shown on top right. If participants choose evac, they cannot make another decision but still can check out all the information.

9. Schedule (Thesis-proposal)

Starting Time	Duration	Objective
September 2019	1 Months	1. Propose the work 2. Implement the control experiments 3. Collecting more hurricane questionnaire if any major hurricanes happen
October - November 2019	3 Months	1. Run the hurricane control experiments 2. Analyse the data 3. Build models for Fox & Grape and Hurricane 4. Two papers for AAMAS: Fox & Grape and Hurricane Model.
December 2019 - January 2020	2 Months	1. Update the model to reflect the data from the first experiment if necessary 2. Potential paper for IJCAI on the hurricane model
February - June 2020	5 Months	1. Write up the thesis 2. Thesis Defence

10. Conclusion

To conclude, I propose a computational model of coping and emotion regulation that unifies decision and emotion. These include a set of assumptions and description which composes of representation and algorithm. The main focus of the work is on exploring different ways of capturing emotion-focused copings, specifically changing beliefs and changing goals, within the decision theoretical framework, namely MDP.

The proposed work also includes the evaluation of the model. The model will be evaluated in two ways: simulation study on fox and grape story, and empirical validation on hurricane situation. The objective of simulation is to explore the consequences of different ways of defining the emotion-focused actions and demonstrate the impact of different components in the model. For empirical validation, we choose hurricane decision as the domain to evaluate the model's predictions on the decision to evacuate or stay, the change of beliefs, and the change of goals. In addition, the data will be used to explore the importance of taking into account the change of beliefs and goals, and the sequential nature of the hurricane event regarding future information in order to predict the decision accurately. The preliminary works have partially evaluated the model on its ability to predict the decision using appraisal dimension. I proposed a set of control hurricane decision experiments that will be used to collect data to evaluate the remaining parts.

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