Uncertainty in the Social World and its Interdependence

Anonymous ACL submission

Abstract

This research investigates the variety of social behaviours that we engage in on a daily basis. There are several unknown factors in each scenario, reflecting the many sources of uncertainty inherent in social judgement. We illustrate how uncertainty emerges in social situations (the thoughts and intentions of others are generally hidden, making predicting a person's behaviour difficult) and why people are driven to reduce the aversive feelings created by uncertainty.We propose a model in which social uncertainty is mitigated first through automatic modes of inference (such as impression generation), before more control-demanding modes of inference (such as perspective-taking) are used to narrow one's expectations even further. Finally, social uncertainty is reduced further by allocating resources to update these predictions based on newer inputs. We propose a novel quantitative framework to provide an account of the mechanisms underlying social cognition and action, by integrating studies from multiple disciplines.

1 Introduction

We frequently find ourselves in circumstances where we must evaluate the impact of our decisions on others, such as how our choices will influence others. Interacting with others is one of the most intrinsically risky activities that humans undertake. There are numerous unknowns, whether it is deciding how to express ourselves, who to confide in, how trustworthy a person is. Hence, it is essential to our productivity, well-being, and, ultimately, our survival as social beings to continually estimate and minimize these uncertainties.

Social psychological research has depicted uncertainty in social environments as pervasive and aversive (FeldmanHall and Shenhav, 2019), which means that specific cognitive processes, such as identifying which categories another person belongs to, help lessen ambiguity (for example, friend or foe). The psychological research domain has advanced our understanding of how people generate predictions regarding the likelihood of future events and their quantitative approach (Sun, 2008) for evaluating uncertainty. We propose a framework to understand factors influencing uncertainty in the social environment. We address the following questions: (i) *what factors give rise to social uncertainty?* (ii) *how do people evaluate and experience uncertainty?* and (iii) *what cognitive tools do they use to resolve it?*.

Our framework is grounded on the rich psychological literature demonstrating that uncertainty helps motivate specific social processes; in psychology, it has been suggested that uncertainty encourages people to make quicker decisions, make first impressions, and stereotype categorisation (such as a colleague, friend, etc. or enemy etc.). This idea was formalised in the Continuum of Impression-Formation model (Fiske and Neuberg, 1990), which suggested that an initial impression is integrated with subsequent information acquired about the person to either confirm the person's category or re-categorise the individual into a new category (Kruglanski, 1990). The follow-up models (Kruglanski et al., 1991; Dijksterhuis et al., 1996) dwelved deeper into the epistemic motivations, to understand why an individual would make use of these processes. Another research (Kruglanski and Webster, 1996) showed that people wanted closure, to reduce ambiguity in their evaluation, as they wanted to perceive their world in a 'clear-cut' way. According to the Need for Closure Model (Festinger, 1957), people are highly keen to receive the information and conclude upon it as an 'eternal judgement', thereby receiving a cognitive closure and eliminating the need to collect more details on the particular situation. Collectively we can presume that psychological research states that there are specific ways in which social uncertainty helps us evolve our behaviour and cognition. In this paper, we describe how computational models simulate cognitive processes involved in social inference (such as the theory of mind) (Baker et al., 2009; Koster-Hale and Saxe, 2013).

2 How do we account for social uncertainty ?

Uncertainty influences the precision of prediction that can be generated based on the available information. As a result, we are capable of being uncertain about everything that our brain attempts to predict, whether it is the interpretation of stimuli (perceptual uncertainty), rewards or punishments (outcome uncertainty), actions to be chosen (action uncertainty), or how those actions will be carried out (motor uncertainty). The different sources of uncertainty are interdependent (Friston, 2010), such that our stimulus can increase the uncertainty about the potential outcomes it predicts and, in turn, heighten our uncertainty about the best possible action. From this point of view, social environments are especially inherently uncertain (Körding and Wolpert, 2006). When interacting with others, our uncertainties about our future states and actions are magnified by the fact that we are frequently uncertain about who these individuals are (their identities, characters, and motives are largely concealed) and how they might choose to act in a given moment. The degree of uncertainty for any prediction can be evaluated in many ways, in terms of variance, entropy and conditional probability. Social uncertainty increases with the increase in number of plausible predictions (Fehr and Camerer, 2007) that we can generate about another person, including their nature, warmth, competence, trustworthiness and many more. Hence theoretically, we can account for social uncertainty from people's perceptions(Kagan, 2009).

3 How do people react to uncertainty ?

A significant study on non-social decision-making has recorded how individuals, groups, and organisations respond to the types of uncertainty. This paper has explained how uncertainty is calculated and how it is used when integrating information from different sources, evaluating future actions and revising expectations based on feedback. Additionally, we have also studied how people navigate uncertainty in their environment. Results reveals that uncertainty tends to trigger negativism (such as anxiety). People perceive uncertainty as aversive, and this motivates them to reduce it.

Further,we have evidence to prove that uncertainty generates (Hirsh et al., 2012; Bach and Dolan, 2012) aversive reaction in both social and non-social events. The key prediction of our model is to differentiate the amount of uncertainty generated in the social and non-social events. Also, the term **"Social Stimuli"** is considered to be more unpredictable than the non-social.

Given the numerous sources of aversive uncertainty that social contexts present, it is not surprising that social stimuli motivate human social behaviour to the degree that they do. This desire to eliminate uncertainty provides a unique view into the kind of cognitive processes that take place in certain social circumstances. According to our concept, people are motivated to think about and act towards others in ways that lessen their own uncertainty and the associated negative affect.

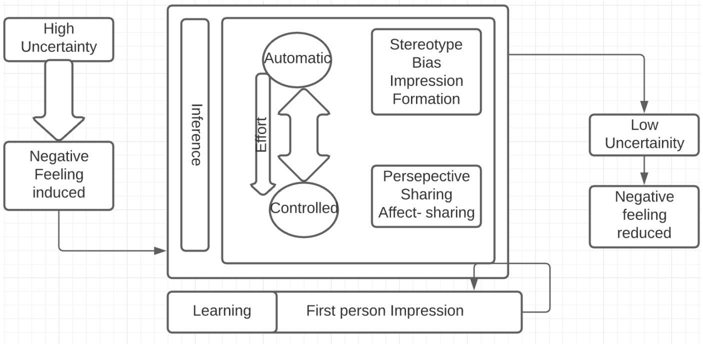

Figure 1: Model to resolve social uncertainty

The above model describe the automatic inference, which means prediction based on the past or controlled inferential process where the predictions on the person's internal thoughts. The learning process keeps updating based on the feedback. These forms of social inference fall in the continuum of automaticity (FeldmanHall and Shenhav, 2019), when processes like perspective-taking and affect sharing differ in the amount of cognitive control, it depends on the individual and the social environment they are presented in.

We propose that social uncertainty motivates three different types of interrelated mechanisms that can help reduce it: relatively automatic inferential processes that rapidly narrow one's predictions using prior knowledge and contextual cues, more control-demanding processes that further evaluate these predictions through an effortful search over person's thoughts and feelings, and learning processes that update one's predictions based on feedback. .

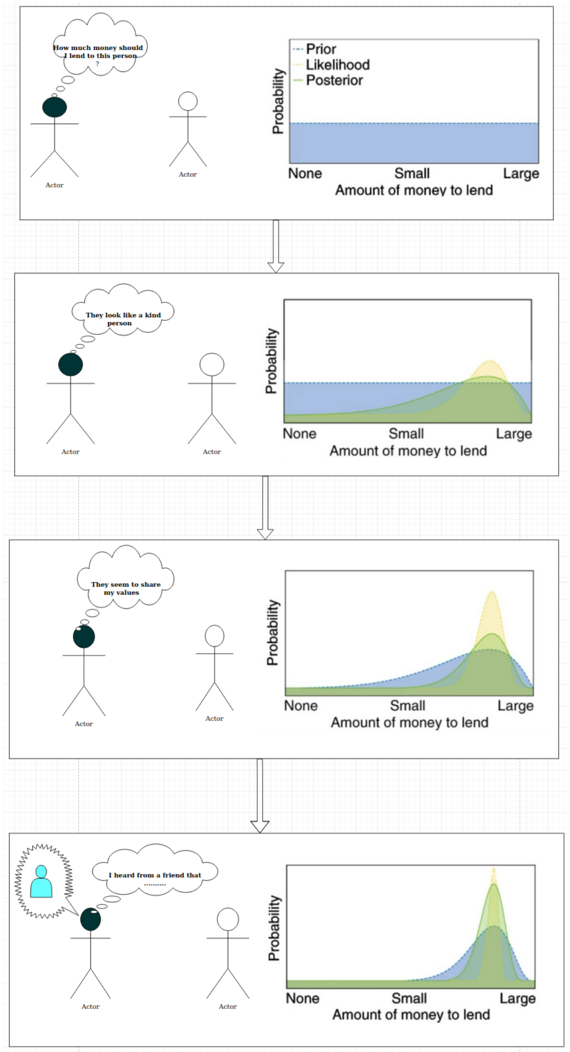

Figure 2: Social Uncertainty through inference and learning: We imagine an individual who seek help from another individual asking for a loan. When deciding how much money to lend, the individual is assigning each possible prediction (e.g. amount of money, how the person looks etc.). The corresponding flat distribution for the predictions (the prior is in blue) represents maximal uncertainty

4 Experimental Design and Procedures

4.1 Entropy and Uncertainty

In this section we discuss how entropy and uncertainty are related and can be used for social cognition. Entropy allows us to make precise statements and performs computations. **Let us assume two independent systems with n and m outcomes, respectively, then the combined system has nm possible outcomes and the expected uncertainty would be the sum of the individual uncertainties. In mathematical terms, it will be represented as follows:**

$$f(nm) = f(n) + f(m) \tag{1}$$

The additivity property validates the independence of the two processes. The property is valid for all positive integers n, m then it is easy to deduce that:

$$f(n) = \log n \tag{2}$$

Thus the uncertainty per outcome is given by, or can be expressed in the term of probability p:

$$\text{uncertainty per outcome } = -p \log p \tag{3}$$

Let us consider a process with n possible outcomes, with probabilities $p_1, p_2, \ldots, p_n$, respectively. Then we can naturally assign uncertainty as $-p_i \log p_i$ to the i-th outcome. This leads us to the hypothesis

$$\text{total uncertainty } = -\sum_{i=1}^{n} p_i \log p_i \tag{4}$$

The above equation is the standard expression for the entropy of the probabilistic process and it is denoted as $H(p)$ or $H(p_1, \ldots, p_n)$. Finally, the entropy is defined as follows:

$$H(p) = H(p_1, \ldots, p_n) = -\sum_{i=1}^{n} p_i \log p_i \tag{5}$$

Next we define social and non social as uncertainty and formulate it using Shannon Entropy. For a probability distribution of a random variable with discrete values defined over $x \in X$, where X is a random variable with n possible outcomes and probability p_i for the i th outcome, $1 \leq i \leq n$. The entropy is thus defined as:

$$S(p) = -\sum_{i=1}^{n} p_i \log_2 (p_i) \tag{6}$$

4.2 Social and Non Social Framework

We create a quantitative framework, by which the social information is incorporated in our predictions. The most critical part is how these predictions will be based on the real time experience of uncertainty by an individual.Here, the uncertainty can be calculated in the form of a psychological entropy or in the terms of the probabilities of discrete outcomes occurring.

$$\text{Entropy } = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{7}$$

We incorporate the social and non social uncertainty as Shannon's entropy:

$$\mathrm{SE} = \mathrm{H(x)} = -\sum_j \Pr(x_j) \cdot \log_2(\Pr(x_j))$$

where Pr is the probability distribution of non-social event and x denotes the outcome of the event j. Entropy is lowest when a single value of x (for example, a particular outcome) is nearly certain, and it increases as there are more values of x (for example, many possible outcomes) that each have increasingly similar likelihoods. Changes in the width of a probability distribution occur as a person's beliefs about their surroundings change, which tends to cause associated changes in the entropy of that distribution. The framework highlights the significant distinctions in uncertainty provided by social vs non-social environments.

We assume that at any given time, there is a distribution of actions a an individual may take given their current state s_y. We can describe their uncertainty over those possible actions in terms of the conditional entropy of this distribution (the entropy over a set of conditional probabilities): **Total uncertainty (nonsocial + social)**

$$f(nonsocial, social) = f(nonsocial) + f(social) \tag{8}$$

$$\begin{aligned} \mathrm{H}(a \mid s_y) = -\sum_j \Pr(a_j \mid s_y) \\ \cdot \log_2(\Pr(a_j \mid s_y)) \cdot \Pr(s_y) \end{aligned} \tag{9}$$

Lets take an example where an individual plans to go to sleep; this kind of action has a much greater likelihood than others (low entropy). When person plans to write a paper, he needs to plan everything, which leads to many more actions (higher entropy). Given our actions, we can determine our future state, but if there is an uncertainty regarding the potential action, it leads to uncertain future states and it brings in a negative state. When another individual (i_z) is present (unknown person), the uncertainty multiplies as one 's own action is dependent on how the other person reacts in any given situation. Uncertainty regarding one's own actions constraints us from evaluating other action in the current state, the situation of uncertainty is interdependent and predicting other persons actions need to to be deconstructed into uncertain attributes.

1. i_z = kind of person or an individual
2. Pr(trait t)= where possible traits $t \in$ { trustworthy, kind, competent, ... }
3. Pr(goal g)= where $g \in$ {asserting dominance, networking, making new friends, ...}
4. Pr(emotion e)= where $e \in$ { happy, angry, disappointed, ...}

Thus, our own uncertainty about how to act in a social setting is influenced by how uncertain we are about each of these social attributes:

$$\begin{aligned} \text{Social Uncertainty} &= \mathrm{H}(a \mid s_y, \text{ trait, goal, emotion, ...}) \\ &= -\textstyle\sum_j \sum_t \sum_g \sum_e \cdots \end{aligned} \tag{10}$$

$$\begin{gathered} \Pr\left(a \mid s_y, \text{ trait}_t, \text{ goal}_g, \text{ emotion}_e, \ldots\right) \\ \cdot \log_2\left(\Pr\left(a_j \mid s_y, \text{ trait}_t, \text{ goal}_g, \text{ emotion}_e, \ldots\right)\right) \\ \cdot \Pr\left(s_y, \text{ trait}_t, \text{ goal}_g, \text{ emotion}_e, \ldots\right) \end{gathered} \tag{11}$$

The possible values for each variable increases, also the uncertainty about how that person might act (E.g.: are they preparing to compliment or being angry), what is our best course of action in that moment and how another might react to our action. Additionally, the potential outcomes that occur by another person's involvement (Example: positive or negative outcome can be formulated as: $\max(|\text{ value}(\text{ outcome } \mid s_y, i)\ |)$.

5 Conclusion

We emphasise the pervasiveness of uncertainty in social world: we are unclear about the intents and behaviours of people we meet, which drives us to be uncertain in social situation. The uncertainty causes negative sentiments, prompting us to want to reduce it, so that we can make our future more predictable. We account the uncertainty in the form of entropy and deconstruct it in the form of social setting. We lay the foundation for future experiments which will shed light on the impact of uncertainty on social cognition.

References

Dominik R Bach and Raymond J Dolan. 2012. Knowing how much you don't know: a neural organization of uncertainty estimates. *Nature reviews neuroscience*, 13(8):572–586.

Chris L Baker, Rebecca Saxe, and Joshua B Tenenbaum. 2009. Action understanding as inverse planning. *Cognition*, 113(3):329–349.

AP Dijksterhuis, AD Van Knippenberg, Arie W Kruglanski, and Carel Schaper. 1996. Motivated social cognition: Need for closure effects on memory and judgment. *Journal of Experimental Social Psychology*, 32(3):254–270.

Ernst Fehr and Colin F Camerer. 2007. Social neuroeconomics: the neural circuitry of social preferences. *Trends in cognitive sciences*, 11(10):419–427.

Oriel FeldmanHall and Amitai Shenhav. 2019. Resolving uncertainty in a social world. *Nature human behaviour*, 3(5):426–435.

Leon Festinger. 1957. *A theory of cognitive dissonance*, volume 2. Stanford university press.

Susan T Fiske and Steven L Neuberg. 1990. A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. *Advances in experimental social psychology*, 23:1–74.

Karl Friston. 2010. The free-energy principle: a unified brain theory? *Nature reviews neuroscience*, 11(2):127–138.

Jacob B Hirsh, Raymond A Mar, and Jordan B Peterson. 2012. Psychological entropy: a framework for understanding uncertainty-related anxiety. *Psychological review*, 119(2):304.

Jerome Kagan. 2009. Categories of novelty and states of uncertainty. *Review of General Psychology*, 13(4):290–301.

Konrad P Körding and Daniel M Wolpert. 2006. Bayesian decision theory in sensorimotor control. *Trends in cognitive sciences*, 10(7):319–326.

Jorie Koster-Hale and Rebecca Saxe. 2013. Theory of mind: a neural prediction problem. *Neuron*, 79(5):836–848.

Arie W Kruglanski. 1990. Lay epistemic theory in social-cognitive psychology. *Psychological Inquiry*, 1(3):181–197.

Arie W Kruglanski, Nathaniel Peri, and Dan Zakai. 1991. Interactive effects of need for closure and initial confidence on social information seeking. *Social Cognition*, 9(2):127–148.

Arie W Kruglanski and Donna M Webster. 1996. Motivated closing of the mind:" seizing" and" freezing.". *Psychological review*, 103(2):263.

Ron Sun. 2008. *The Cambridge handbook of computational psychology*. Cambridge University Press.