

# Is Uncertainty Always Bad?: Effect of Topic Competence on Uncertain Opinions

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**Abstract**—The proliferation of information disseminated by public/social media has made decision-making highly challenging due to the wide availability of noisy, uncertain, or unverified information. Although the issue of uncertainty in information has been studied for several decades, little work has investigated how noisy (or uncertain) or valuable (or credible) information can be formulated into people’s opinions, modeling uncertainty both in the quantity and quality of evidence leading to a specific opinion. In this work, we model and analyze an opinion and information model by using Subjective Logic where the initial set of evidence is mixed with different types of evidence (i.e., pro vs. con or noisy vs. valuable) which is incorporated into the opinions of original propagators, who propagate information over a network. With the help of an extensive simulation study, we examine how the different ratios of information types or agents’ prior belief or topic competence affect the overall information diffusion. Based on our findings, agents’ high uncertainty is not necessarily always bad in making a right decision as long as they are competent enough not to be at least biased towards false information (e.g., neutral between two extremes).

**Index Terms**—Subjective logic, uncertain opinion, information credibility, prior belief, and topic competence.

## I. INTRODUCTION

Decision making under uncertainty becomes more challenging as we are living with flooding amounts of unverified information provided by public/social media, and/or interpersonal interactions in an individual’s online/offline social network. Many existing studies have examined the key factors that impact the dynamics of opinions in different domains. In the mass communication, perceptions of news credibility from public media (e.g., newspapers, online news, television, radio) have been studied to investigate if there exists any link between the change of public opinion and the perception of public media news [9]. In the network science, a rich amount of literature investigated how the choice of seeding nodes propagating initial information affects information diffusion [5, 12]. However, little work has studied how individuals process uncertain, noisy information, how their topic competence (e.g., expertise or knowledge on a given topic) affects processing of noisy (or uncertain) or valuable (or credible) information, and the subsequent results of these factors on the opinions and beliefs of individuals.

In this work, we develop an agent-based opinion and information model by considering agents processing information differing in its bias (e.g. supporting a pro or con point of view) and in its value (e.g. noisy vs. valuable)

and forming opinions with a degree of uncertainty. In this work, we define the concepts of ‘noisy’ and ‘valuable’ in terms of uncertainty and credibility, respectively. In particular, the concept of uncertainty indicates *vagueness* (i.e., unclear without reasonable, analytical reasoning or clear facts) and/or *ambiguity* (i.e., inconsistency with conflicting evidence) which may not be useful for agents to collect credible evidence supporting either pro or con. On the other hand, the concept of credibility refers to conciseness and consistency that can provide a clear stance by providing clear, factual details based on a rational, analytical reasoning process [7]. However, credible information is not necessarily true as we can find information that looks credible and real but it turns out to be false. This is why we consider the four types of information, given either pro or con can be true. In cases where there is a clear true point of view, we declare one of pro vs. con points of view to be correct. While there exists work in belief models (e.g., Subjective Logic) to tie uncertainty in beliefs to both quantity and balance of information supporting pro or con points of view, there is no model that also incorporates quality of information and an agent’s ability to assess quality into opinion models. However, the interplay between these two dimensions is a crucial aspect of dissemination of biased and incorrect information in today’s social networks and has not been widely studied.

This work has the following **key contributions**:

- We develop an agent-based opinion and information model which allows the agent to form a uncertain opinion based on Subjective Logic (SL) and to process information different along two different dimensions in order to explicitly deal with uncertainty in its opinion. Our model allows four types of information, modeled along with *pro* ( $P$ ) vs. *con* ( $C$ ) and *noisy* ( $N$ ) vs. *valuable* ( $V$ ) dimensions, as detailed in Section III-C. To the best of our knowledge, no prior work has considered the formulation of SL-based opinions that can accept these types of information which can be easily found in reality.
- We model agents’ topic competence which can significantly affect their information processing in diagnosing given evidence on whether it is noisy or valuable and their decisions on whether to accept false information after interacting with other agents. This allows us to analyze the effect of agents’ topic competence on the

degree of agents' belief in false information under the various information scenarios.

- We conduct comprehensive simulation experiments in order to identify key factors that can increase the fraction of agents not believing in false information, given that 'belief' in SL represents false information. Our findings show that uncertainty is not necessarily always bad in making a right decision when agents are capable of not being biased for false information such as having a neutral stance in their prior belief/disbelief towards the given topic.

## II. BACKGROUND & RELATED WORK

In this section, we discuss existing work on decision making under uncertainty and information credibility in public/social media. We also give a brief overview on approaches to mitigate or remove false information propagation in social networks.

### A. Uncertainty in Decision Making

Many state-of-the-art studies have investigated how decision makers use other alternative methods to deal with uncertainty in decision making such as herding [1, 2, 16] or cognitive bias [15, 19]. However, no prior work has investigated how an individual agent forms its uncertain opinion in processing information composed of credible (or valuable) or uncertain (or noisy) evidence, which is explored in this work.

### B. Information Credibility in Public/Social Media

Many approaches to derive information credibility have been studied using social media datasets. Castillo et al. [4] developed a credibility methodology by identifying a set of features representing false information propagated through Twitter. Sikdar et al. [17] proposed a methodology that combines both direct and heuristic evaluations of credibility with superior performance to the baseline counterparts. However, these studies do not model or track change in opinions of individuals and their uncertainty given a ground truth of information credibility.

### C. Countering False Information Propagation

Existing approaches to counter false information use two main approaches: *network analysis-based approach* (NA) and *feature-based approach* (FA). NA aims to stop false information propagation by selecting a set of counter-misinformation nodes (i.e., nodes to disseminate true information against misinformation) [14]. The process of misinformation is also modeled based on epidemic models with variants of SIR (Susceptible-Infected-Recovered) model by introducing 'forgetting/remembering factor' in rumor propagation [21]. FA concentrates on identifying key features of false information or the sources (i.e., users) of the false information in gossip diffusion [20] and feature extraction for rumor identification [10].

Unlike the existing approaches in both NA and FA, this work examines uncertainty of opinions in analyzing the propagation of information considering agents' topic competence, prior belief and their opinion updates based on information composed of the four different types as discussed earlier.

## III. OPINION MODEL

In SL, an *opinion* is represented by three dimensions: *belief* ( $b$ ), *disbelief* ( $d$ ), and *uncertainty* ( $u$ ) [8]. A single opinion on a given proposition is represented by:

$$b, d, u \in [0, 1]^3, \quad b + d + u = 1 \quad (1)$$

We adopt SL to explicitly deal with uncertainty an agent perceives in updating its opinion.

### A. Opinion Formation

The agent may have degrees of belief (i.e., agree or pro) and/or disbelief (i.e., disagree or con) towards a given proposition with some degree of uncertainty. Agent  $i$ 's opinion on proposition  $A$  is denoted as  $w_i^A$ . For simplicity, we omit  $A$  and use  $w_i$  to represent an agent  $i$ 's opinion as  $w_i = \{b_i, d_i, u_i, a_i\}$  where  $a_i$  is the base rate which normally represents general background knowledge or judgment bias [8].

The base rate,  $a_i$ , affects expectation probability (i.e., a probability that an agent is expected to make a decision) in either belief or disbelief [8], denoted by  $E_{b_i}$  or  $E_{d_i}$ , respectively, where they are given by:

$$E_{b_i} = b_i + a_i u_i, \quad E_{d_i} = d_i + (1 - a_i) u_i. \quad (2)$$

Note that  $E_{b_i} + E_{d_i} = 1$  as  $b_i + d_i + u_i = 1$ . An individual's acceptance towards given information is affected by various factors, including personality (e.g., agreeableness, open-mindedness, stubbornness), impact of neighbors (e.g., herding), homophily (e.g., like-mindedness), competence (e.g., domain knowledge), or confidence (e.g., certain about its own opinion). In this work, we particularly model and analyze the effect of individuals' topic competence on a given proposition in which the topic competence may adjust the degree of the prior belief and affect final decisions.

In SL, an agent forms its opinion based on the amount of directly observed evidence based on the following mapping rule:

$$b = \frac{r}{r + s + W}, \quad d = \frac{s}{r + s + W}, \quad u = \frac{W}{r + s + W}. \quad (3)$$

where  $r$  is positive evidence and  $s$  is negative evidence for a particular proposition. For simplicity, we dropped the subscript  $i$  denoting the agent. When  $W = 0$ ,  $b$  is a natural estimate of the fractional evidence in favor of the proposition. To be specific,  $W$  indicates the amount of uncertainty introduced by the inherent errors or imperfect observability.

### B. Opinion Update

In this section, we describe how our work modeled the following: (i) the impact of an agent's topic competence on its prior belief/disbelief; (ii) homophily-based (i.e., like-minded) opinion update; and (iii) opinion decay over time. We adopt the features of (ii) and (iii) from our prior work [6] and include them here to be self-contained.

1) *Prior Belief based on Topic Competence*: An agent's topic competence is defined as the critical thinking ability which can be against bias or prior belief even if such belief is generally accepted by others in the network [18]. As this work models this characteristic as a parameter, each agent  $i$  is characterized by its own topic competence  $tc_i$ , ranged in  $[0, 1]$

as a real number, which is used for agent  $i$  to judge if given information is valuable or noisy or if the prior belief or prior disbelief,  $a_i$  or  $1 - a_i$ , is properly supporting given information (e.g., given information is true or false).  $tc_i$  also affects how much agent  $i$  is for/against its prior belief/disbelief favoring pro or con,  $a_i$  or  $1 - a_i$ , depending on its judgmental ability to diagnose true/false information. Assuming that given belief,  $b_i$ , represents the degree that  $i$  believes false information,  $i$ 's prior belief can be adjusted based on its competence  $tc_i$  by:

$$\hat{a}_i = (1 - (tc_i - 0.5))a_i \quad (4)$$

where  $\hat{a}_i$  is the adjusted prior belief while the prior disbelief is  $(1 - \hat{a}_i)$ . Note that this is the case assuming that a given belief represents the support for false information which is denoted by *pro* while a given disbelief indicates not believing the false information, denoted by *con* in the scenario considered in this work. Recall that the adjusted prior belief/disbelief,  $\hat{a}_i/(1 - \hat{a}_i)$ , will replace  $a_i/(1 - a_i)$  in Eq. (2), which significantly impacts agents' final decision in pro/con. Eq. (4) implies that when agent  $i$  has high competence,  $i$  is less likely to believe in false information. Note that  $tc_i = 0.5$  implies that the original prior belief is used as intact (i.e.,  $tc_i = 0.5$ ) and there is a chance for the prior belief to increase when  $tc_i < 0.5$ . This indicates that when an agent has below the average competence (i.e.,  $tc_i = 0.5$ ), an agent's bias can be even more pronounced. On the other hand, its bias can be relaxed with the high competence when it is above the average competence (i.e.,  $tc_i > 0.5$ ).

2) *Homophily-based Opinion Consensus*: Homophily, or like-mindedness, significantly affects the way people update opinions [13]. In this work, the similarity of two agents' opinions, denoted by  $s_i^j$ , is computed based on *cosine similarity* of the two opinion vectors  $i$  and  $j$  in terms of their belief and disbelief,  $(b_i, d_i)$  and  $(b_j, d_j)$ , respectively. The calculation of  $s_i^j$  based on the cosine similarity is omitted due to its popularity and space constraint.

We use  $s_i^j$ , as a discounting operator [8], to determine the degree to which agent  $i$  accepts agent  $j$ 's opinion. Given two vectors of opinions,  $w_i = \{b_i, d_i, u_i\}$  and  $w_j = \{b_j, d_j, u_j\}$ , agent  $j$ 's trust opinion in  $i$ 's opinion,  $s_i^j$ , is given by  $w_{i \otimes j} = \{b_{i \otimes j}, d_{i \otimes j}, u_{i \otimes j}\}$  where each element is estimated by:

$$b_{i \otimes j} = s_i^j b_j, \quad d_{i \otimes j} = s_i^j d_j, \quad u_{i \otimes j} = 1 - s_i^j(1 - u_j). \quad (5)$$

where  $u_{i \otimes j}$  is simply derived by  $u_{i \otimes j} = 1 - b_{i \otimes j} - d_{i \otimes j}$  and  $b_j + d_j + u_j = 1$ . For simplicity, we omit the time step notation, but both sides of the equation refer to time step  $t$ .

We use SL's *consensus* operator [8] for an agent's opinion update upon receiving new information. The updated opinion of agent  $i$  after interaction with agent  $j$  is denoted as  $w_i \oplus b_{i \otimes j} = \{b_i \oplus b_{i \otimes j}, d_i \oplus d_{i \otimes j}, u_i \oplus u_{i \otimes j}\}$  and each element is given by:

$$\begin{aligned} b_i \oplus b_{i \otimes j} &= \frac{b_i u_{i \otimes j} + b_{i \otimes j} u_i}{\beta}, \\ d_i \oplus d_{i \otimes j} &= \frac{d_i u_{i \otimes j} + d_{i \otimes j} u_i}{\beta}, \\ u_i \oplus u_{i \otimes j} &= 1 - (b_i \oplus b_{i \otimes j} + d_i \oplus d_{i \otimes j}). \end{aligned} \quad (6)$$

where  $\beta = u_i + u_{i \otimes j} - u_i u_{i \otimes j}$  and  $\beta \neq 0$  is assumed. We omit the time step notation; the left side represents  $w_i(t + 1)$  while the right side uses the opinions at  $t$  such as  $w_i(t)$  and  $w_j(t) = w_{i \otimes j}(t)$ .

3) *Opinion Decay over Time*: Unless an agent receives new information by interacting with other agents, its opinion decays over time based on a decay factor,  $\gamma$ , over belief and disbelief while uncertainty increases in proportion to  $\gamma$ . For example, human cognition is limited by forgetting information over time. We model the decayed opinion by:

$$b_i = (1 - \gamma)b_i, \quad d_i = (1 - \gamma)d_i, \quad u_i = u_i + \gamma(1 - u_i). \quad (7)$$

Note that  $u_i$  is simply derived based on  $1 - b_i - d_i$  where  $b_i + d_i + u_i = 1$ . Different from the opinion update by Eq. (6) which allows the opinion update only for  $\beta > 0$  and  $u_i > 0$ , respectively, the opinion decay based on Eq. (7) occurs at every time step. Therefore, even if  $u_i$  reaches 0, over time it can increase (i.e.,  $u_i > 0$ ) and accordingly agent  $i$  can update its opinion upon receiving new information from its neighbors. For simplicity, we omitted the time step notation, but the left side is at time  $t + 1$  while the right side is at  $t$ .

### C. Information Model

When an agent receives information from public/social media (e.g., news articles shared), it discerns if the received information is credible or not. To model Quality-of-Information (QoI) representing information credibility in the received information, we adopt the information model used in [7] where QoI is presented by the following four aspects of information: (1) *noisy* information without any reasonable, analytical reasoning or clear facts; (2) *valuable* information with clear, factual details based on a rational, analytical reasoning process; (3) information to support *pro* for a given proposition (e.g., believing a false rumor); and (4) information to support *con* against a given proposition (e.g., disbelieving a false rumor).

Recall that valuable (or credible) information is not necessarily true. Regardless of the actual truthfulness of information, information can be noisy or valuable. We consider the four categories of information [7] as:

- *Pro / Valuable (PV)*: Information supports pro for given information and is valuable.
- *Pro / Noisy (PN)*: Information supports pro for given information but is noisy.
- *Con / Valuable (CV)*: Information supports con for given information and is valuable.
- *Con / Noisy (CN)*: Information supports con for given information but is noisy.

In this paper, we propose a novel method to incorporate this information model to SL. We formulate the QoI based on Beta distribution [8] considering the degree of uncertainty as an opinion (see Eq. (3)),  $\mathcal{Q} = \{q_b, q_d, q_u\}$ , in SL treating the amount of CN and PN as the amount of uncertain evidence (i.e.,  $W$  in Eq. (3)) where the number of PV as the amount of evidence to support a pro (i.e.,  $r$  in Eq. (3)), and the number of CV as the amount of evidence to support a con (i.e.,  $s$  in

Eq. (3)). In reality, a human with limited cognitive capability cannot capture the ground truth information. How to perceive information (e.g., noisy vs. valuable) is significantly affected by an agent's competence, prior belief or bias. We define an agent's perceived opinion  $\hat{Q}_i = \{q_{b_i}, q_{d_i}, q_{u_i}\}$  based on its *topic competence*,  $tc_i$ . Note that agents' topic competence  $tc_i$  also affect the degree of their prior belief as described in Eq. (4). The agent's perceived opinion,  $\hat{Q}_i$ , is estimated based on the mapping rule (Eq. (3)) where the number of *perceived* positive, negative, and uncertain evidence by agents is obtained by Algorithm 1 which returns  $n_b$ ,  $n_d$ , and  $n_u$ , respectively. Given  $n_s = n_b + n_d + n_u$ , each element of an opinion  $\hat{Q}_i$  is given by:

$$q_{b_i} = \frac{n_b}{n_s}, \quad q_{d_i} = \frac{n_d}{n_s}, \quad q_{u_i} = \frac{n_u}{n_s}. \quad (8)$$

In Algorithm 1, we assume that an agent can perfectly judge whether evidence is *pro* or *con*, but cannot perfectly know whether it is valuable or noisy. Hence, it uses its competence,  $tc_i$ , to judge the evidence's value (noisy or valuable). This opinion,  $\hat{Q}_i$ , is used to initialize the opinions of original propagators who first receive public/social media information and disseminate it to its neighboring agents in a network.

#### IV. AGENT MODEL

This work considers an online social network as a directed or undirected graph  $\mathcal{G}$  where vertices,  $v_i$ 's, are agents  $i$ 's (e.g., users) in the set of  $\mathcal{V}$  and the edges,  $e_{ij}$ 's (i.e., 1 for an edge and 0 for no edge), represent the relationships in the set  $\mathcal{E}$ . Agent  $i$ 's neighbors refer to other agents directly connected to  $i$ . In this work, a network is initialized with a set of agents receiving information from public/social media. Then, the agents propagate their opinions based on the received information to its neighboring agents (i.e., directly connected agents). The neighboring agents propagate their opinions further over a network. Hence, after the initial set of seeding agents propagate their own opinions formed based on their competence which processes the four types of evidence, the information propagation continues until every agent has a chance to propagate its own opinion (i.e., not the original opinion from the original propagator) to its neighbors. This way of the opinion propagation is to reflect the reality that people tend to talk about their own opinions, not necessarily what they exactly heard from others or media upon interactions with others.

##### A. Agent Types

We have two types of agents as follows:

- *Originators* (Os): This agent  $i$  is selected to receive media information which consists of both noisy and valuable information. Its opinion vector  $\{b_i, d_i, u_i\}$  is set to  $\{b_i, d_i, u_i\} = \{q_{b_i}, q_{d_i}, q_{u_i}\}$  based on Eq. (8). A set of original propagators (Os),  $s^*$ , is initially selected before the interactions between agents. This type of agents does not change for the whole session after they form their opinions based on Eq. (8).
- *Propagators* (Ps): This agent  $i$  has low confidence (i.e.,  $u \rightarrow 1$ ) in its own opinion by not initially agreeing

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#### Algorithm 1 Mapping Evidence to an Opinion

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1: procedure [ $n_b, n_d, n_u$ ] = MAPEVIDENCE( $tc, \mathbf{EVD}$ )
2:    $tc$ : an agent's topic competence
3:    $\mathbf{EVD}$ : a matrix of evidence (4 columns for PV, PN, CV, CN
   and  $t$  rows for time steps from  $t = 1, \dots, T$ ) where evidence is
   mapped to one of the four types of evidence, it is 1; 0 otherwise
   (e.g., [1, 0, 0, 0] represents the evidence is PV)
4:    $n_b = 0$ : counter for # of evidence supporting belief
5:    $n_d = 0$ : counter for # of of evidence supporting disbelief
6:    $n_u = 0$ : counter for # of of uncertain evidence, supporting
   neither belief nor disbelief
7:    $T$ : Number of evidence
8:   for  $t = 1$  to  $T$  do
9:      $r = rand()$  ▷ a random real number in [0, 1] based on
   uniform distribution
10:    if  $\mathbf{EVD}(t) == 1$  then
11:      if  $r \leq tc$  then ▷ knows evidence is valuable
12:         $n_b \leftarrow n_b + 1$ 
13:      else
14:         $n_u \leftarrow n_u + 1$ 
15:      end if
16:    else if  $\mathbf{EVD}(t) == 2$  then
17:      if  $r \leq tc$  then ▷ knows evidence is noisy
18:         $n_u \leftarrow n_u + 1$ 
19:      else
20:         $n_b \leftarrow n_b + 1$ 
21:      end if
22:    else if  $\mathbf{EVD}(t) == 3$  then
23:      if  $r \leq tc$  then ▷ knows evidence is valuable
24:         $n_d \leftarrow n_d + 1$ 
25:      else
26:         $n_u \leftarrow n_u + 1$ 
27:      end if
28:    else ▷  $\mathbf{EVD}(t) == 4$ 
29:      if  $r \leq tc$  then ▷ knows evidence is noisy
30:         $n_u \leftarrow n_u + 1$ 
31:      else
32:         $n_d \leftarrow n_d + 1$ 
33:      end if
34:    end if
35:  end for
36: end procedure

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or disagreeing with given information (i.e.,  $b \rightarrow 0$  and  $d \rightarrow 0$ ). This agent is initialized with its opinion with  $(r, s, W) = (1, 1, n)$  where  $n \gg 1$ , leading to  $\{b_i, d_i, u_i\} = \{\frac{1}{n+2}, \frac{1}{n+2}, \frac{n}{n+2}\}$ , implying low confidence in a given proposition due to lack of information (i.e., ignorance). This type of agents keeps updating their opinions unless its uncertainty  $u$  reaches 0, based on SL's consensus operator in Eq. (6).

As discussed in Section III-B, uncertainty can increase as an opinion decays over time as shown in Eq. (7). For simplicity, we adopt the high effectiveness (influence) property [3] assuming that when  $j$  propagates its opinion to its neighbor  $i$ , then  $i$  will accept it with perfect probability (i.e., 1) and accordingly update its opinion unless  $i$  is an originator.

##### B. Epidemic Status of Agents

We model the evolution of false information propagation using a variant of the SIR model [6]. The three states in the SIR model are defined based on the conditions associated with

TABLE I: Key parameters and their default values

param.	val.	param.	val.	param.	val.
$n$	1000	$(tc_\mu, tc_{std})$	(0.5, 0.1)	$\gamma$	0.05
$s^*$	$N \times 0.01$	$(a_\mu, a_{std})$	(0.5, 0.1)	$n_r$	100

TABLE II: Network dataset statistics

$N$	1033	Ave. degree	51.785	Ave. path length	2.949
$ \mathcal{E} $	26747	Modularity	0.54	Ave. clustering coeff.	0.534

the expected belief or disbelief probabilities,  $E_{b_i}$  and  $E_{d_i}$ , as follows:

- *Susceptible* ( $\mathcal{S}$ ): An agent is not sure of whether it believes false information or not. Agents in  $\mathcal{S}$  have opinions with  $E_b \leq 0.5$  and  $E_d \leq 0.5$ ;
- *Infected* ( $\mathcal{I}$ ): An agent believes false information as true with  $E_b > 0.5$ ; and
- *Recovered* ( $\mathcal{R}$ ): An agent does not believe false information with  $E_d > 0.5$ .

## V. NUMERICAL RESULTS AND ANALYSIS

In this section, we describe metrics used for the experiments and detailed experimental setup. We also analyze the experimental results and discuss their overall trends.

### A. Metrics

- *Agents' average opinion*: This metric shows the average value of an opinion with three dimensions, belief, disbelief, and uncertainty. Since the scenario is that belief indicates an supporting opinion for given false information, lower belief and higher disbelief are desirable while the degree of uncertainty will play a role in increasing/decreasing belief/disbelief.
- *Fraction of recovered agents* ( $\mathcal{R}$ ): Based on the SIR model used in our work (see Section IV-B), this metric refers to the fraction of agents which are in the status of the recovered ( $\mathcal{R}(t)$ ) over all propagators. This metric indicates the fraction of agents that do not believe false information with  $E_d > 0.5$ .

### B. Experimental Setup

For the network topology, we use an ego-Facebook dataset [11] which gives a fully connected undirected network described by Table II. To disseminate the original public information by a given set of originators, we seed 1 % of the total nodes, denoted by  $s^*$ , which is 11 nodes in the given network and model the rest of the nodes (i.e., 1022) as propagators. We consider opinion decay factor  $\gamma$  set to 0.05 and mean prior belief  $a_\mu = 0.5$  with the standard deviation  $a_{std} = 0.1$ , implying that both prior belief and prior disbelief are fairly same. Agents' topic competence is assigned with the mean  $tc_\mu = 0.5$  with the standard deviation  $tc_{std} = 0.1$ . The key design parameters and their default values used for our experiments are summarized in Table I. The data points shown in the results are the average values based on the collected data from simulation runs  $n_r = 100$ .

Information propagation proceeds as follows. A given number of originators,  $s^*$ , is initiated with the set of opinions,  $\hat{Q}$  as described in Section III-C. After the originators form their opinions by processing the four types of evidence, PV, PC, CV, and CN, they propagate their opinions to their neighbors. Accordingly, the neighbors also forward their updated opinions

to their neighbors based on Eq. (6). Note that each agent has a chance to disseminate its opinion to its neighbors. We discuss the effect of the key design parameter values on the given metrics in Section V-A in the following section.

### C. Results and Analysis

In this section, we conduct sensitivity analysis by varying the values of key design parameters, mainly including varying the ratio of information types (i.e., # of PV, PN, CV, and CN) and the degree of agents' topic competence.

1) **Effect of Varying the Amount of Valuable Information (PV and CV)**: Fig. 1 shows how the amount of valuable evidence (i.e., #PV and #CV) affects agents' mean opinion in terms of three dimensions, denoted by  $b$ ,  $d$ , and  $u$ , and the fraction of recovered agents ( $\mathcal{R}$ ). In Fig. 1 (a) showing the mean  $b$ , the increase of #CV decreases  $b$  because more uncertain evidence is introduced by agents' imperfect topic competence (i.e.,  $tc_\mu = 0.5$ ). However, as #PV increases,  $b$  increases with relatively less uncertain evidence, as seen in Fig. 1 (c). In addition, the increasing trends of  $b$  is observed as #CV increases with higher #PV ( $\geq 5000$ ) because of the decreasing uncertain evidence  $u$  based on the increased amount of valuable evidence. However, with higher #CV ( $\geq 4000$ ),  $b$  decreases again due to the increased uncertain evidence introduced by imperfect competence used to detect noisy or valuable evidence. In Fig. 1 (b), we show the effect of varying #CV and #PV in  $d$ . As expected, higher #PV shows the lowest  $d$  while the increase of #CV increases  $d$  overall. In Fig. 1 (b), lower #PV and/or higher #CV increases  $d$  which is intuitively true. In Fig. 1 (c), we show  $u$  as #CV and #PV increase. Under relatively low #PV (i.e., #PV  $\leq 2000$ ), we can see increasing uncertainty with higher #CV because of the imperfect topic competence. However, under relatively higher #PV, higher #CV decreases  $u$  due to the increased effect of  $d$ . In particular, when #PV = 6000, the minimum point of  $u$  at #CV = 4000, which is generated based on the tradeoff between  $b$  and  $d$  because of  $b + d + u = 1$ . Finally, Fig. 1 (d) shows the fraction of recovered agents,  $\mathcal{R}$ , where an agent is identified as *recovered*, meaning that the agent does not believe false information,  $b$ , with  $E_d > 0.5$ . From this figure, we can clearly observe the positive effect of #CV, showing that higher #CV increases  $\mathcal{R}$ , because its misdetection can increase uncertainty which is also considered in calculating expected disbelief in Eq. (2). In addition, higher #PV is also clear by decreasing  $\mathcal{R}$ . The noticeable finding is that the imperfect topic competence increases uncertain evidence which can allow agents to make right decisions (disbelieving false information) because they are not at least biased for false information  $b$ . However, the increased uncertainty does not allow  $d$  or  $\mathcal{R}$  to increase further.

2) **Effect of Varying the Amount of Noisy Information (PN and CN)**: Fig. 2 shows how the noisy information (i.e., #CV and #CN) affects  $b$ ,  $d$ ,  $u$ , and  $\mathcal{R}$  when agents are given with the mean topic competence,  $tc = 0.5$ . Very similar to the trends observed in Fig. 1, the effect of #CN is clearer in  $b$  with lower #PN and in  $d$  with higher #PN. That is, higher #PN significantly mitigates the positive effect of higher #CN,

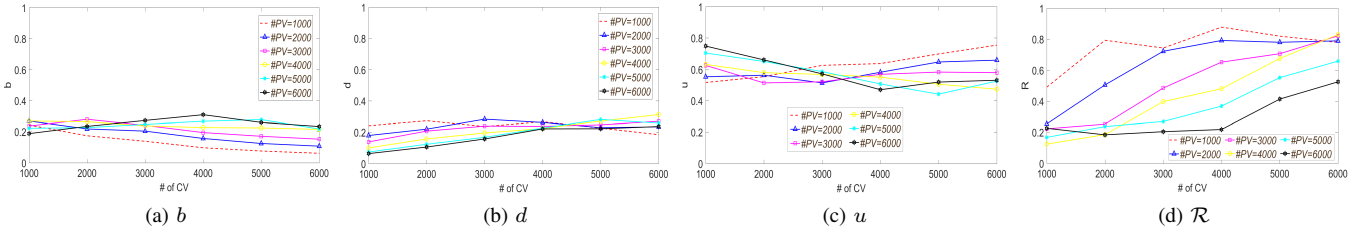


Fig. 1: Effect of varying the amount of valuable information

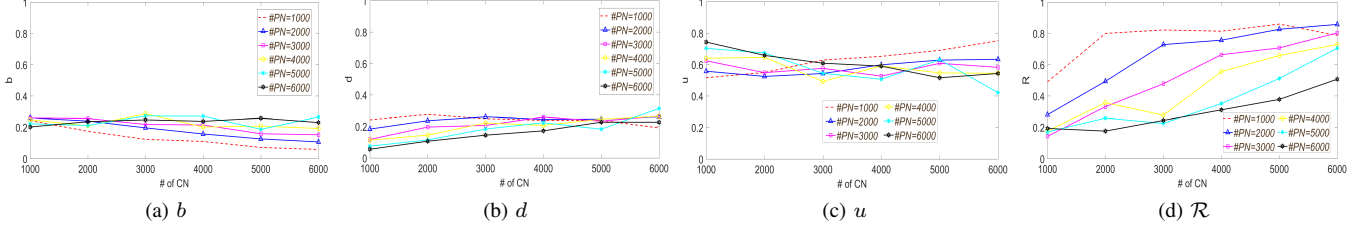


Fig. 2: Effect of varying the amount of noisy information

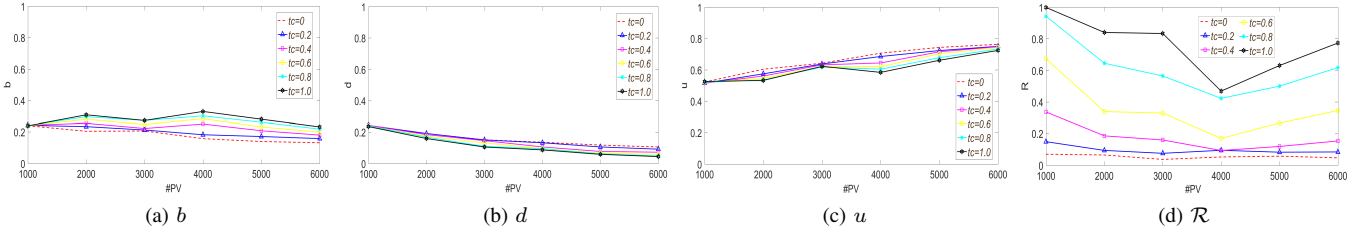


Fig. 3: Effect of the topic competence under varying the amount of valuable *pro* evidence (PV)

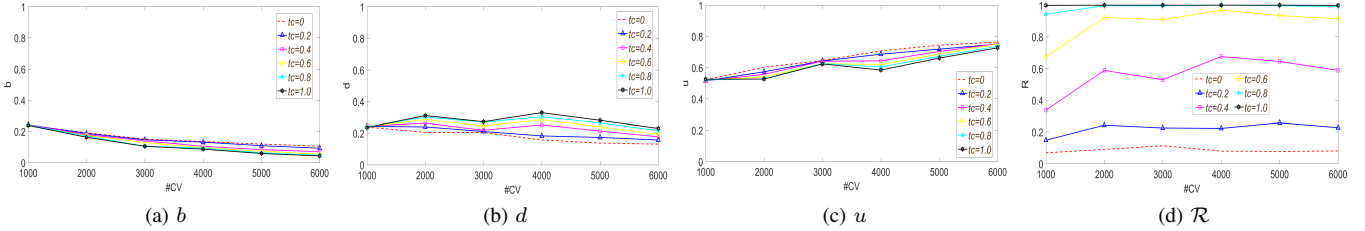


Fig. 4: Effect of the topic competence under the amount of valuable *con* evidence (CV)

detecting half valuable con and half noisy con which lead to higher  $d$ . Overall the effect of noisy information is very similar to that of valuable information although the effect of valuable information slightly shows the better performance in  $\mathcal{R}$ . Now we discuss the effect of varying agents' topic competence as below.

3) **Effect of Varying the Amount of Agents' Topic Competence under Varying the Amount of PV:** Fig. 3 shows how agents process their opinions and update them based on their different topic competence with respect to varying #PV when #CV, #CN, and #PN are fixed at 1000. From this figure, we find very interesting results because the trends of  $b$  and  $d$  look counter-intuitive. But the reasons can be well explained in terms of the amount of uncertain evidence diagnosed based on agents' topic competence given. To be specific, in  $b$  shown in Fig. 3 (a), the lowest topic competence (i.e.,  $tc = 0$ ) shows the lowest  $b$  while the highest topic competence (i.e.,  $tc = 1$ ) shows the highest  $b$  because  $tc = 0$  takes all  $b$  and  $d$  evidence (i.e., #PV and #CV) as uncertain evidence,  $u$ , resulting in too high uncertainty generated, as

shown in  $u$  shown in 3 (c). Similarly, the effect of significantly increased  $u$  is observed in  $b$  (3 (a)), showing the highest  $b$  with  $tc = 1$ . The increased  $b$  with  $tc = 1$  also reduces  $d$  as  $b + d + u = 1$ . When  $tc = 1$ , only noisy information (1000 #PN and 1000 #CN) is counted as uncertain evidence while others will be either  $b$  or  $d$ . Thus, uncertainty with  $tc = 1$  is the lowest. That is, compared to the increased  $tc$  that reduces agents' prior belief (see Eq. (4)) and lessens  $b$  but increases  $d$ , the largeness of increased uncertain evidence,  $u$ , exceeds the effect of reduced prior belief, resulting in higher  $b$  and lower  $d$  with high  $tc$  where #PV is larger than any other evidence types.

4) **Effect of Varying the Amount of Agents' Topic Competence under Varying the Amount of CV:** Lastly, Fig. 4 shows the effect of agents' topic competence with respect to varying #CV when #CN, #PV, and #PN are set to 1000. Recall that based on Algorithm 1, the correct detection of #CV means that the evidence is detected as valuable con information (i.e., true information) while misdetection of #CV means that the evidence is detected as uncertain evidence. Unlike Fig. 3

showing that higher  $tc$  generates more  $b$  and less  $d$  as #PV increases, the effect of #CV follows the intuitive results such that higher  $tc$  generates more  $d$  and less  $b$ , leading to higher  $\mathcal{R}$ . As mentioned earlier, this trend is reasonable because higher #CV means more valuable evidence to support  $con$  which corresponds to  $d$  while generated uncertain evidence due to imperfect topic competence from given #CV can increase  $\mathcal{R}$  as well.

## VI. CONCLUSION

The key findings are summarized as follows:

- An appropriate amount of valuable information (e.g., #CV) exists to maximize valuable evidence to support truth while minimizing uncertain evidence.
- The amount of uncertain evidence can help when agents are not at least biased favoring for false information (i.e.,  $b$ ), meaning that agents' base rate,  $a_i$ , does not exceed 0.5, resulting in higher  $\mathcal{R}$ .
- When the amount of false evidence (e.g., #PV) exceeds that of true evidence (e.g., #CV), higher  $tc$  may increase the amount of false information,  $b$ . However, since higher  $tc$  can reduce the effect of false information,  $b$ , by using lower prior belief in the false information, higher  $tc$  can achieve higher  $\mathcal{R}$  even with more valuable evidence supporting false information with the help of uncertain evidence which is interpreted as not supporting the false information.
- When the amount of true evidence (e.g., #CV) exceeds that of false evidence (e.g., #PV), higher  $tc$  helps increase  $d$  and accordingly  $\mathcal{R}$ . This is because even misdetection of true evidence can increase the amount of uncertain evidence which can be well utilized to increase expected disbelief, leading to higher  $\mathcal{R}$  with the reduced bias towards false information with higher  $tc$ .

The future work directions of this research can follow: (i) the investigation on the effect of centrality types of information originators in various network topologies; (ii) the improvement of designing agents' prior belief (i.e., base rate) to dynamic prior belief based on all prior evidence; and (iii) the development of uncertainty detector by examining text mining techniques which can be used for the validation of the presented opinion and information model.

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