Abstract—Trust and reputation are significant components in open dynamic systems for making informed and reliable decisions. State-of-the-art information fusion models that exploit these mechanisms generally rely on reports from as many sources as possible. Situations exist, however, where seeking evidence from all possible sources is unrealistic. First, querying information sources is costly especially in resource-constrained environments, in terms of time, bandwidth. Secondly, reports from multiple sources exposes one to the risk of double-counting evidence, introducing an extra challenge of distinguishing fact from rumour. This paper describes TIDY, a trust-based approach to information fusion that exploits diversity among information sources in order to select a small number of candidates to query for evidence, and to minimise the effect of correlated evidence and bias. We demonstrate that reliable decisions can be reached using evidence from small groups of individuals. We show empirically that our approach is robust in contexts of variable trust in information sources, and to a degree of deception.

I. INTRODUCTION

Effective decision-making in large, open, and dynamic systems relying on information from sensors is plagued by uncertainty due to unreliable information from these sources. Sensory sources can be soft (e.g., humans, organisations) or hard (e.g., wireless sensors), and their reliability may be impaired either by extreme operating conditions and use of poor quality devices (wireless sensors), or through incompetence and deceptive behaviour (humans). As sensors, and indeed other data and information sources (e.g., databases and open data on the Internet) become ubiquitous within the environment, assets owned by different stakeholders have the potential of exchanging observations and information, in order to extend their coverage and to make more informed decisions. Stakeholders may maintain different levels of trust amongst one another that influence their information sharing policies.

While many existing information fusion protocols assume that all the information sources are reliable [12], other approaches exist, that adopt methods in trust and reputation systems to address uncertainty, and maximise confidence in fused information [14], [23]. However, using trust and reputation to improve the quality of fusion, requires paying close attention to challenges such as constraints in resources and correlated evidence, which are often overlooked. In particular, state-of-the-art models exploiting these mechanisms generally rely on reports from as many sources as possible, as more evidence minimises the risk of biased opinions. In the physical world, capturing and distributing evidence can be costly. For instance, in distributed environments such as peer-to-peer networks, sensor networks, pervasive computing, each participant is responsible for collecting and combining evidence from others due to lack of central authority or repository. Also, in emergency response, a decision maker normally reasons with high volumes of streaming information, with strict real-time requirements. The major constraints in these systems are bandwidth, delay overheads, and energy, motivating the need to minimise the number of messages exchanged in order to arrive at a decision. Furthermore, there is often no guarantee that evidence obtained from the sources are based on direct, independent observations. Sources may likely provide (unverified) reports obtained from other sources (e.g., copying in social networks, ‘gossiping’ in sensor networks [5]), resulting in correlations and bias. Consequently, although combining reports from multiple sources is useful, effective sampling of information sources in order to improve the quality of information fusion and therefore the overall effectiveness of decision-making requires answering some important questions: With limited capacity to query for evidence, how can reliable decisions be reached using evidence from small groups of individuals? How can one ensure that opinions from diverse sources based on their private experience are taken into consideration, without the risk of double-counting evidence? Using a small subset of sources to arrive at decisions is non-trivial in large, open, and dynamic systems as known and trusted sources may leave the system at some point, and unknown and possibly unreliable sources may join the system. This clearly intuits a certain trade-off between exploration of the population of (possibly unknown) information sources and exploitation of known and trusted sources [13].

In an attempt to address these issues, we present a trust-based approach to information fusion, that exploits diversity among information sources to sample them, in ways that maximise the quality of assessments and minimise the costs of arriving at decisions. Our approach involves grouping homogeneous sources (likely to provide similar evidence) together in order to minimise the number of sources consulted for evidence. In this paper, we further our initial work in [7].

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TIDY: A Trust-Based Approach to Information Fusion through Diversity
In these scenarios and others that may be similarly drawn, an objective report may be detrimental to their well-being. Policies of their individual affiliations, especially if providing subjective logic as the underlying information fusion and trust model that exploits diversity to sample a small group of sources for evidence in contexts of uncertain and deceptive information sources. Finally, we leverage the power of subjective logic as the underlying information fusion and trust assessments framework. We demonstrate the effectiveness of our approach against existing methods in both making more accurate assessments, and using fewer resources.

The rest of this paper is organised as follows. Section II provides some background on the concept of diversity and also highlights related work in the area. In Section IV we introduce TIDY, our information fusion framework, and in Section V we present evaluation of our approach. Finally, we conclude in Section VI with a discussion and avenues for future research.

II. BACKGROUND

Humans and indeed any entity operating in a social space, are profoundly affected by the interaction of individuals and the social networks that link them together. Evidence of such pattern has emerged in literature, and is referred to elsewhere as herd thinking [19]. This describes a situation where no one is thinking, but everyone is just copying (or conforming with) everyone else. While this phenomenon may not be observed in all domains or even regarded in terms of copying, however, in most information dissemination environments such as social media (such as Facebook, Google+, and Twitter), individuals are linked together by different affiliations (features), that define how information is accessed and propagated between them. For example, Facebook defines the concept of friends, in which neighbours can access and further propagate (possible without any acknowledgement) opinions obtained from their friends. Google+ and Twitter defines such relationships as circles and followers respectively. In other settings such as news media, individuals may maintain similar opinions simply because they learned about such from their favourite news channels (e.g., CNN, BBC, Fox News). Furthermore, in coalition contexts, different stakeholders may maintain different policies that determine the sort of information they share with others, and exactly how such information are being shared [1]. For example, information sources from a certain country or organisation involved in a peace-keeping mission may add subjectivity to shared information in line with operating policies of their individual affiliations, especially if providing an objective report may be detrimental to their well-being. In these scenarios and others that may be similarly drawn, one may likely find revealing patterns in source features that correlate with their behaviour.

To generalise on this concept, one might potentially infer that information sources with similar features may likely provide similar reports in certain contexts. For example, individuals subscribing to similar channels for their news feeds are more likely to align their opinions in a similar pattern. Similarly, it could be inferred that sensors positioned within the same physical location or under the same administrative domain may provide similar reports. If such hidden relationships exist between features of sources and the reports they provide, one might exploit diversity to limit the number of sources consulted for evidence, and protect oneself against correlations of evidence and bias. The argument here is that, if a group of sources is observed to consistently provide similar reports, then such group could be viewed as a single entity, representing a single view point. Consequently, we define diversity as a function $\Delta: 2^S \rightarrow G$ mapping different subsets of sources to a set of groups of homogeneous sources. This process involves learning appropriate similarity metrics that may be used to stratify the population of sources, and allows us to group sources likely to provide similar reports together based on their features.

There are several studies on source diversification and trust assessments in fused information. The truth finder systems in [21], [6], assume a prior knowledge of the similarity metric for source diversification. Specifically, [21] exploits the follower-followee relationship in Twitter as a metric for source diversification. In most cases, however, such prior knowledge may not be available especially in large, open and dynamic systems, where relationship between sources may be defined by many dimensions. In [3], the correlation between features and behaviour of sources is exploited with an emphasis on estimating trustworthiness of unknown sources for the purpose of task delegation. A bayesian model is proposed in [16] for the purpose of interpreting the subjectivity in evidence obtained from sources. The evaluation function of a source is learned by exploiting its features, however, this work does not consider the problem of double-counting of evidence, which could seriously undermine the quality of assessments made by the system.

III. PRELIMINARIES

In this section we formally introduce the problem statement, and present some necessary terminologies and formulae that are used later in the paper.

A. Sampling Budget

The aim of our system is to support the selection of reliable information sources within budgetary constraint in order to improve the quality of information fusion. Formally, given some budget $\Phi$, and a set of potential information sources $C$, the objective is to select a subset of sources known as the fusion set $C \subseteq \mathcal{S}$, such that the decision maker’s evaluation function $E(C, Cost_C(q, \rho, R_C, \Phi))$ produces a sufficiently high quality of information. The optimal subset of sources to sample reports from, given a budget $\Phi$, can be characterised as the subset that maximizes the expected utility of a query $q$:

$$C_{\text{opt}} = \arg \max_{C \subseteq \mathcal{S}} E(C, Cost_C(q, \rho, R_C, \Phi)),$$  \hspace{1cm} (1)
where $R_C$ is the set of reports obtained from sources in $C$ in response to a query $q$. $\text{Cost}_C$ is defined as a function of individual costs of the sources in $C$ as $\text{Cost}_C(q) = \sum_{s \in C} \text{Cost}_s(q)$.

The sampling constraint is specified such that $\text{Cost}_C(q) \leq C$. 

**B. Subjective Logic**

We present a brief primer on subjective logic (SL) used in this paper for evidence combination. More details about SL is presented in [9]. Subjective logic is a type of probabilistic logic that explicitly takes uncertainty and belief ownership into account. In general, SL is suitable for modelling and analysing situations involving uncertainty and incomplete knowledge. Arguments in SL are subjective opinions about propositions. A binomial opinion of an agent $x$ about the truth of a proposition $\rho$ is represented by the quadruple $\omega^x_\rho = (b, d, u, a)$, where: $b$ is the belief that $\rho$ is true; $d$ is the belief that $\rho$ is false; $u$ is the uncertainty about $\rho$; and $a$ is the base rate, and represents the a priori probability about the validity of $\rho$ in the absence of any evidence. The default value of $a$ is 0.5 [10], which means that before any positive or negative evidence has been received, both outcomes are considered equally likely. $b + d + u = 1$ and $b, d, u, a \in [0, 1]$. A binomial opinion can be represented as a Beta distribution. Opinions are formed on the basis of positive and negative evidence. The variables $i$ and $j$ represent the number positive and negative observations about $\rho$ respectively, and can be used by $x$ to obtain an opinion about $\rho$ as follows:

$$b = \frac{p}{p + q + 2}, \quad d = \frac{q}{p + q + 2}, \quad u = \frac{2}{p + q + 2}.$$  \hfill (2)

The probability expectation value of an opinion is defined as:

$$E(\omega^x_\rho) = b + u \times a.$$  \hfill (3)

**IV. SYSTEM DESCRIPTION**

Fig 1 illustrates the key components of TIDY, our information fusion framework. It assumes there is one information consumer or decision maker $x$, that uses reports from different sources to arrive at decisions. The decision maker may be working under specific budget constraints, and therefore needs to devise effective means of sampling the sources for evidence. The sources may be owned by a number of different stakeholders, with varying degrees of trust. In addition, sources may not always report based on their direct, independent observation, and may only be relaying information obtained from others, or as specified by different information sharing policies. In the more malicious setting, some sources may coordinate to provide similar information in order to reinforce their opinion in the system. The purpose of TIDY therefore, is to aid the decision maker in improving the quality of its assessments given all these challenges by sampling sources and fusing evidence in an effective manner. To assist the decision maker achieve this goal, the framework is equipped with a trust model based on subjective logic, that enables the discounting of reports to reflect the perceived reliability of the reporting source. The diversity model (DM) component uses suitable similarity metrics to stratify the source population, such that similar sources are grouped together. The source selection module, uses knowledge of source diversity to sample the population of sources for evidence according to the allowed budget. Issues of correlation are handled in the fusion process by exploiting knowledge provided in the DM. The knowledge base (KB) holds feedback after observing the ground truth with respect to a specific fusion output. KB also holds evidence about the behaviour of sources in different groups with respect to similarity of their reports. Based on the evidence obtained, both the trust and the diversity models are updated to reflect current knowledge. In the case of DM, this may trigger a learning process in order to keep the model consistent. In the rest of this section, we present the formal description of aspects of the system, and also describe in detail how the different processes highlighted are implemented.

**A. Information source**

We denote as $S$ the set of information sources accessible to $x$. Information source $s$ is a tuple $(Id, F, R)$, where $Id$ is a unique identifier, $F$ is a set of features, and $R$ is a set of past reports. Let $F$ denote a finite set of features belonging to a source, such that $f_1, f_2, \ldots, f_d \in F$. Feature is an observable attribute of a source e.g., organisational affiliation or location of the source. Some sources might be more similar based on their features, and over time, the decision maker learns the relative importance of features represented by the vector $w^s_1, w^s_2, \ldots, w^s_d$, where $w^s_i$ is $s$’s view of the importance of feature $f_i$ in defining similarity among a group of sources, and $w^s_i :\rightarrow [0, 1]$. Subsequently, $x$ uses this metric to stratify the population of sources. A detailed description of this process is presented in Section IV-D.

**B. Report**

A report $R$, is an opinion provided by a source $s$, about an event $\rho$ to the decision maker $x$, in response to a query $q$. A source $s$, records its perceived opinion about $\rho$ as $R^t_{s,\rho}$, and reports $R^t_{s,\rho}$ when queried by $x$. The variable $t$ corresponds to a specific sampling round or time step associated with a report from $s$, such that $R^t_{s,\rho}$ represents a report at time $t$. $R^t_{s,\rho}$ is the set of reports received by $x$ from $s$ in the interval $t$, $t + k$. We assume that the same query $q$ is made to all the sampled sources in a specific sampling round $t$. A report is numerical value drawn from a Gaussian distribution and its interpretation depends on $\rho$. For example, $R^t_{s,\rho} = 0$ is interpreted differently for queries “is agent $x$ trustworthy?” and “how many terrorists exit in the theatre?”.

**C. Group**

Let $G$ denote a stratification on $S$, and $g_1, g_2, \ldots \in G$. We define a group $g_i \in G$ as a collection of homogeneous information sources, such that $\{s : s \in g_i, g_i \in G\} = S$. Groups do not overlap, and a valid stratification is one in
which a source belongs in only one group. Groups are formed subjectively by an agent $x$, who attempts to disambiguate what metrics lead to a better stratification of sources. The aim of partitioning the population is to provide a suitable generalisation of information sources using different distinguishing characteristics. Subsequently, the agent exploits this model to limit the number of sources queried for evidence, and to protect itself against evidence double-counting and deception. Detailed description of group formation process is presented in Section IV-D. Sources are grouped together based on how similar they are to one another, as specified by some similarity metric. For example, it may have been learned over time that sources such as sensors with feature batteryLow mostly provide false opinions about an event, or that sensors owned by certain organisations usually obfuscate their reports before sharing. Such distinguishing characteristics may be used by an agent to form a model of the sources, and subsequently exploited in future encounters with members of the group. It is important to emphasise here that group membership does not capture a semblance of sources simply based on their level of trustworthiness, rather it is a measure of the consistency of sources in giving similar reports in response to queries. Also, although sources grouped together may be regarded as having similar level of trustworthiness, having similar level of trustworthiness alone does not satisfy the condition for diversity. For instance, it is possible for sources in different groups to have similar level of trustworthiness (e.g. sources from different, but equally reputable organisations).

The second stage involves using the learned metric to partition sources in the same group giving similar reports is maximised. The best feature-behaviour correlation, such that the likelihood of positive evidence (conflicting with $qT$) $q$ is 2. Based on this evidence, the trust $\tau$ for $s_{1}$ is computed. Fig.2b represents the similarity relationship for the sources, and shows the report similarity score $\varphi$ for each source pair after five sampling rounds, which is based on their reports in Fig.2a. Similarly, Equations 2 and 3 is also used to compute $\varphi$, whereby positive evidence $p$ represents instances a source pair gives similar reports, and negative evidence $q$ is those instances the pair gives dissimilar reports. Based on this the report similarity is computed for the pair. Although the three sources are considered to be equally reliable with a trust score of 0.57 after five sampling rounds, however, their reporting pattern is not similar in the sampling period considered. Sources $s_{1}, s_{3}$ appear more consistent in providing similar reports as indicated in the high similarity value ($\varphi=0.85$) than any other pair.

A trust score is maintained for each group $g_{i}$, and is used by the decision maker as an expected reliability of members encountered in the group. First, the trust score $\tau_{s,p}$ of each individual member is calculated as demonstrated in the previous example. The group trust $\tau_{g_{i},p}$ is then calculated using Equation 4 as average of individual member’s trust score.

$$\tau_{g_{i},p} = \frac{\sum_{s \in g_{i}} \tau_{s,p}}{|g_{i}|}$$

(4)

**D. Learning Diversity**

As earlier mentioned, our goal in diversity is to find the best way of stratifying the population of sources, such that similar sources are grouped together as specified by their features. In diversity learning, our aim is therefore to identify a function $\Delta : 2^{S} \rightarrow G$ that maps different subsets of sources to a set of groups. We take as a working assumption, that there may be some correlation between the features of sources and their reports. Where this exists, we could exploit information from observable features of sources, as well as evidence from their past reports to learn similarity metrics that may be subsequently used to diversify the source population. To explain the learning process, we adapt our illustration in Fig. 2 and use as a running example in the rest of the paper. We assume a peace-keeping mission, with 100 sources each monitoring the level of conflict in a specific region. Reports on ground situation provided by the sources when queried by the decision maker $x$ are expressed in terms of numeric values in the range $[0, 1]$, where 0 implies no conflict state, and 1 high conflict state, which may warrant the deployment of troops to the region to manage the situation. Let’s also assume that $x$ has historical evidence of the sources reports, and therefore wishes to learn the best way of diversifying the population, so as to carry out an effective sampling in future interactions with the sources. Each source is identified by 6 features, as perceived by $x$, and these are labelled $f_{1}, f_{2}, ..., f_{6}$, where features may represent attributes such as country, location, expertise, etc., and coded by numeric values.

![Fig. 3: Example model tree and classification rule for diversity.](image-url)

To build a model of diversity, $x$ performs a two-stage process. The first stage is an attempt at disambiguating what metrics lead to a better stratification of the population. A good metric in our estimation is one that produces the highest feature-behaviour correlation, such that the likelihood of sources in the same group giving similar reports is maximised. The second stage involves using the learned metric to partition the sources into semi-homogeneous subgroups. We make use of existing machine learning techniques in both instances and learn associations between sets of features, represented...
as numeric attributes, and a target value (similarity score) defining the degree of similarity between sources. Specifically, we employ the M5 model tree learning [15] algorithm\(^1\) to build a regression model to estimate similarity between sources and the hierarchical clustering [17] algorithm\(^2\) to build groups of similar sources based on the learned similarity model.

Fig. 3 shows an example model tree and classification rule for the diversification of the 100 sources. The model is constructed using the M5 algorithm for predicting similarity between sources, and generalises to new and unknown sources. The algorithm shares some similarities with decision tree classifiers (CART), which builds tree-based models for classification. However, unlike CART with class labels or values at the leaves, the leaves of a model tree are multivariate linear regression models, which are used to predict a target value (in our case, a similarity score \(M\)). Input to the M5 algorithm is a collection of training instances. Each instance is specified by its value of a fixed set of attributes. For example, to add a training instance, we compute the similarity (1 - absolute difference of corresponding attributes i.e., \(1 - |f_i^1 - f_i^2|\)) of each of the 6 attributes for each source pair \((s_1, s_2)\), and the class, which is the report similarity in a given time interval \(T\) for the source pair. While computing the report similarity, we define a similarity threshold \(\eta\), and compute report similarity as a function of the number of similar reports \(p\), and dissimilar reports \(q\) for the source pair, for all relevant time steps \(t \in T\).

\[
D_{s_1, s_2}^R = |R_{s_1} - R_{s_2}|. 
\]

\[
(p_{s_1, s_2}, q_{s_1, s_2}) = \begin{cases} 
(1,0), & \text{if } D_{s_1, s_2}^R \leq \eta. \\
(0,1), & \text{otherwise}.
\end{cases} 
\]

\[
p_{s_1, s_2} = \sum_{t \in T} p_{s_1, s_2}, \quad q_{s_1, s_2} = \sum_{t \in T} q_{s_1, s_2}. 
\]

The report similarity \(\varphi\) for \((s_1, s_2)\) pair is then computed using Equations 2 and 3. \(D_{s_1, s_2}^R\) in Equation 5 is the difference between reports of \(s_1, s_2\) for a specific sampling time \(t\).

In the second stage of the process, we use the learned metric to stratify the population of sources. We employ the hierarchical clustering algorithm for this task, and define a stoppage criteria or diversity threshold, \(\delta\) for clustering. The \(\delta\) parameter which lies in the interval \([0,1]\), specifies the maximum level of diversity required in the system. For instance, if the parameter is \(\delta = 1\), all the sources are assigned to singleton groups (no diversity). However, if \(\delta\) is too low (i.e., \(< 0.5\)), all sources are assigned to one group (extreme diversity). The clustering process uses the linear regression models constructed by the M5 algorithm to predict the similarity (specified by \(M\)) for each source pair, and subsequently uses this measure to cluster the sources. Therefore, given the feature vector of any two sources as input, a similarity score \(M\) is obtained that specifies the degree of ‘closeness’ of the pair. Specifically, this is obtained by using the most relevant linear regression model for the evaluated instance as illustrated in Fig. 3. With this information the clustering process proceeds as follows. Each source is initially regarded as belonging to a separate cluster, and the two clusters with the highest similarity score \(M\) are continuously merged to form a new cluster until the stoppage condition \(\delta\) is met. The similarity score of a cluster is computed as the average similarity of all member pairs in the cluster.

E. Sampling and Fusion of Reports

The diversity model offers rich context from which a fusion set may be derived. In general, a fusion set is made of candidates randomly selected from different groups, whose combined evidence is used to form an opinion. Depending on the specific task requirements, richer contexts could be explored using the learned diversity of the source population. For instance, the cost and risk assessments of a potential transaction, may influence the sampling process. Members in a group comprising of trustworthy sources may be favoured, for example, over sources in less trustworthy groups in a high-risk transaction. Also, in situations where the cost associated with sampling from specific groups of sources (e.g. groups of experts) exceeds a budget, groups of less knowledgeable sources may be considered, who in combination may provide a sufficiently similar quality of information. Irrespective of the sampling alternatives considered, a key objective is to maintain a reasonable view of the different sub-groups in the population, so as to have a competitive exploratory advantage of the population. Given this requirement, we present two methods for selecting candidate sources to make up the fusion set. The choice between both methods is dependent on the available budget \(\Phi\), and the number of sub-groups identified.

We assume budget \(\Phi\) can be expressed in terms of the number of sources that may be sampled for a specific query \(q\). The fusion set \(C\) comprises of candidates for fusion sampled from various groups in \(G\). Let \(G \subseteq G\) denote the subset of groups in \(G\) whose members are to be included in \(C\), such that \(\{G_i : G_i \subseteq g, G_i \in G\} = C\). This implies that \(G_i\) is the corresponding subset of sources sampled from group \(g\), and \(C\) then translates to the union of all the candidate groups which are contained in \(G\). We may have two different cases:

**CASE I** (\(\Phi \geq |G| \implies G = G\)): This method has some similarities with the proportion allocation technique of stratified random sampling [4]. The number of candidates to be sampled from a group \(G_i\) based on the budget:

\[
budget(g_i) = |g_i| \times (\Phi/|S|) 
\]

Representative candidates are then randomly selected from \(g_i\) according to \(\text{budget}(g_i)\), and these are contained in \(G_i\). Applying this technique directly however, may lead to information exclusion in much smaller groups (e.g. not selecting from singleton groups), therefore, we constrain our specific implementation to the selection of at least one candidate from each group, by reducing the number of candidates to be sampled from much larger groups.

**CASE II** (\(\Phi < |G| \implies G \subseteq G\)): Using this method, a single representative candidate is selected from each group, by ranking the groups in order of trustworthiness. Assuming groups are ordered in descending order of trust scores, then \(\text{budget}(g_i) = 1\), if group rank > \(\Phi\), and \(\text{budget}(g_i) = 0\), if group rank ≤ \(\Phi\). The intuition here is that, although information is potentially lost from some of the groups, however,
it is more profitable to prioritize available resources to more trustworthy sources, and increase the scope of exploration as the budget increases.

Provided the likelihood of sources in each of the groups behaving in a similar manner is relatively high, then evidence from the fusion set using either methods described above may be considered a sufficient representation of the entire population. However, we do not suggest these to be the only methods for sampling, but only that both techniques demonstrate possible realisation of our model, which we have used in our evaluation. Other sophisticated sampling techniques may be explored to meet specific information requirements.

Reports from the fusion set $C$ are combined in order to form an opinion about $\rho$. Specifically, the reports from the sources are first partitioned into different units to correspond with their groups. The consensus opinion of each group is calculated by computing the mean report in the group $R_{g\times\rho}$, as in Equation 9. The resulting opinions are then discounted by the corresponding trust score $\tau^e_{G_i\times\rho}$ of the groups. Finally, the normalized opinions from all groups are then combined to obtain the overall opinion $E^e_\rho$. This fusion approach minimises the adverse effect of large groups of unreliable sources working together to undermine the trustworthiness of the fusion results. The process is concisely formalised in Equation 9.

$$R_{G_i\times\rho} = \frac{\sum_{s \in G_i} R_{s \times \rho}}{|G_i|}, \quad E^e_\rho = \sum_{G_i \in G} \sum_{s \in G_i} \tau^e_{G_i\times\rho}$$

V. Evaluation

We have evaluated our approach through a set of simulations. Our evaluation focused on the effectiveness of TIDY in guiding the decision maker in making reliable decisions, for instance to know when to deploy troops to a conflict region, based on reports from third-party sources monitoring the ground situation. In particular, we measure the robustness of the framework in the presence of reports from varying degrees of unreliable sources, who are particularly coordinated in reporting. We divide the simulations into two sets, one that studies the effect of different budget constraints in the presence of experts (honest and malicious). Report types are defined as follows.

- **Honest report**: This type of report is closer to the ground truth, with small Gaussian noise $N(0,0.01)$. Sources with high reliability ratio $P_r$ are more likely to provide this type of report when queried.
- **Malicious report**: Malicious sources with low $P_r$ are more likely to provide this type of report, which, if left unmanaged could potentially undermine the fusion result. Reports in this category are significantly deviated from the ground truth, with large Gaussian noise $N(1,0.01)$.

At the end of each round, the decision maker learns the ground truth and updates the trustworthiness of the sources with new evidence computed using Equation 10, which is based on the intuition that information is still useful if it has a small amount of noise or is slightly discounted [18].

$$(x', y') = \begin{cases} (1,0), & \text{if } |gT^* - R^*| \leq 0.1 \\ (0,1), & \text{otherwise} \end{cases}$$
Different experimental conditions are considered, which evaluates the performance of the system with different sampling budgets $\Phi$. To keep things simple in our simulations, $\Phi$ is interpreted in relation to the number of sources that may be sampled for evidence. In each of our simulations, we define a small budget with $\Phi = 5$ and large budget with $\Phi = 75$, to indicate that fusion decisions may be based on evidence sampled from 5 and 75 sources respectively. Since we are considering fusion of information in large and open environments, sources can freely join and leave the system. We simulate this property of the system with the parameter $P_l$, which determines in each round the probability of a particular source leaving the environment. When a source leaves, it is replaced with a new source of the same profile, in order to keep the number of sources fixed throughout the simulation. This property impacts on the ability of the different trust-based fusion methods to accurately learn the reliability of all the sources, and emphasis the need for good trade-off between exploration and exploitation of sources. However, dynamic activity is relaxed in all cases for first 30 rounds, in order to enable the different approaches gather information to build bootstrap their models. The parameter list with their default values is shown in Table I.

**A. Results**

Each of our simulations is repeated 10 times, with each run made up of 100 sampling rounds. We present the average of our results, which are significant based on analysis of variance (ANOVA) with repeated measures, having a confidence interval of 0.95. Error bars show variation between means.

![Fig. 4: Increasing percentage of malicious sources with different budget ($\Phi$) constraints](image)

**1) Robustness to deception with experts:** In this set of simulations, we demonstrated the robustness of our TIDY approach against other methods with varying degree of deception. We show results for the two budgets types in Fig. 4. The majority based approach MBS starts off better than other approaches in all cases when the ratio of malicious sources is low in the system. This is because MBS benefits from the large number of honest reports to filter out malicious ones. Also it is not affected by the dynamic nature of sources in the system, as its filtering is based only on statistics on the reports and not on knowledge of the sources themselves. However, with increasing number of malicious sources, this approaches degrades significantly, since it is not robust in the face of large number of malicious reports. The slight performance lag in the case of TIDY and OBS when fewer malicious sources are present in the system as compared to MBS is due to the discounting of opinion by learning the reliability of sources over time, which might take some time to converge, coupled with uncertainty introduced by source dynamism $P_l$. Therefore, lower weights might be attached to reports of highly trustworthy sources, and this impacts on the resulting fusion results. However, the benefits of observation based filtering becomes obvious as the ratio of malicious sources in the system increases. Effect of bogus reports is greatly mitigated due to acquired knowledge of behaviour of the sources. An interesting observation is in the performance of both TIDY and OBS when the budget is increased. Although performance might be expected to improve with increasing sampling allowance, however, our results show a different case. Increasing budget in the case of OBS gives a slight performance boost when malicious sources are in the minimum ($\leq 20$), however, performance degrades significantly when malicious sources increase. This can be explained by the effect of the $P_l$ parameter. As OBS is interaction based, and exploits only highly trustworthy sources, in situations that known and trustworthy sources leave the system, OBS wrongly represents weight assigned to unknowns sources. Without any interaction, the trustworthiness of sources, even highly trusted sources is computed as 0.5 (total uncertainty). Performance of TIDY remains relatively stable with changing budget, and outperforms all the other approaches, because although known and trustworthy sources may leave the system, TIDY does a good job finding alternative trustworthy sources to sample through the exploration capability of its diversity component.

![Fig. 5: Increasing percentage of dependent sources with different budget ($\Phi$) constraints](image)

**2) Robustness to deception with non-experts:** Often times the degree of corroborations of evidence is used as an indication of trustworthiness, especially in systems where there no clear experts. In such scenarios for example, one would likely believe an event reported by numerous sensors more than conflicting evidence supplied by one or few sensors. This is the case in applications such as crowdsourcing and citizen sensing, were information is often sought from numerous and mostly unreliable sources. If those sources are simply relaying what they heard from others, then this may lead to misinformation. In this set of experiments, we demonstrate the robustness of our
approach to varying degree of source dependence (copying). In these experiments, there are no clear experts therefore, and the decision maker may rely on the degree of corroboration of reports to determine the ground truth. In this case, we vary the proportion of sources depending on others for opinion from 0 to 90, and present the results in Fig. 5, with different sampling budgets as before. In this setting, sampling based on majority filtering MBS becomes significantly misleading since it generally assumes independence among the sources, whom although copying, may not be depending on opinions from reliable sources. The fused opinions is distorted, and inadequate for filtering out outliers. NBS gains some performance improvement over MBS, but still does badly in general. OBS does significantly better than the other two approaches, but worse than TIDY, since without the presence of consistency of source behaviour, it is unable to model the reliability of sources effectively to discount their opinions. TIDY on the hand performs better, because although its trust component does little in learning source trustworthiness, however, its diversity component is able to identify dependencies among the sources and uses this to inform its fusion process.

VI. CONCLUSION AND FUTURE WORK

We have presented a framework for sampling information sources and fusing information in environments where resource limitations and restrictions need to be taken into consideration. Our approach effectively balances the trade-off between exploration and exploitation of information sources and is particularly useful in scenarios where a decision maker is exposed to the risks of deception and double-counting of evidence. Deception and report correlations have been shown to greatly degrade the quality of information fusion, and therefore needs to be mitigated to enhance confidence in fusion results. Where hidden networks or patterns defining correlated behaviour exist in the population, our approach is able to uncover such, and subsequently exploit it in order to limit the number of information sources sampled. Where naive approach of information fusion would perform poorly under these conditions as revealed in the simulation results, our model shows positive outcomes that outperform classical trust-based information fusion approaches within budgetary constraints. We have identified the need to incorporate more robust decision-theoretic mechanisms to handle complex source selection strategies, so as to meet different information needs. Our current work operates on static information, where the assessed situation is assumed to remain fairly stable over time. We intend to extend our study to address dynamic settings where information is streamed by a number of sensory sources and the assessed situation is assumed to remain fairly stable over time. We intend to extend our study to address dynamic settings where information is streamed by a number of sensory sources and the assessed situation is assumed to remain fairly stable over time. We intend to extend our study to address dynamic settings where information is streamed by a number of sensory sources and the assessed situation is assumed to remain fairly stable over time. We intend to extend our study to address dynamic settings where information is streamed by a number of sensory sources and the assessed situation is assumed to remain fairly stable over time. We intend to extend our study to address dynamic settings where information is streamed by a number of sensory sources and the assessed situation is assumed to remain fairly stable over time.