Algorithmic Transparency of Conversational Agents

Sam Hepenstal
Middlesex University
London
SH1966@live.mdx.ac.uk

Neesha Kodagoda
Middlesex University
London
N.Kodagoda@mdx.ac.uk

Leishi Zhang
Middlesex University
London
L.X.Zhang@mdx.ac.uk

Pragya Paudyal
Middlesex University
London
P.Paudyal@mdx.ac.uk

B.L. William Wong
Middlesex University
London
W.Wong@mdx.ac.uk

ABSTRACT

A lack of algorithmic transparency is a major barrier to the adoption of artificial intelligence technologies within contexts which require high risk and high consequence decision making. In this paper we present a framework for providing transparency of algorithmic processes. We include important considerations not identified in research to date for the high risk and high consequence context of defence intelligence analysis. To demonstrate the core concepts of our framework we explore an example application (a conversational agent for knowledge exploration) which demonstrates shared human-machine reasoning in a critical decision making scenario. We include new findings from interviews with a small number of analysts and recommendations for future research.

CCS CONCEPTS

• Information systems → Information systems applications; **Decision support systems**; **• Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Explainable AI; Graph Analysis; Conversational Agents

ACM Reference Format:
Sam Hepenstal, Neesha Kodagoda, Leishi Zhang, Pragya Paudyal, and B.L. William Wong. 2019. Algorithmic Transparency of Conversational Agents. In *Joint Proceedings of the ACM IUI 2019 Workshops, Los Angeles, USA, March 20, 2019* , 11 pages.

1 INTRODUCTION

With advances in artificial intelligence (AI) technologies, reasoning like cognitive processes are no longer restricted to the human mind. In cases this has led to shared human-machine reasoning, where both parties are able to explore information by interpreting, inferring, and learning, before reaching a common understanding. One example of shared reasoning can be found in conversational agent applications which reason from semantic knowledge graphs. These applications are the focus for this paper, however, the principles identified within the framework presented also apply to other types of application which exhibit shared human-machine reasoning for critical decision making.

1.1 Focus Study: Conversational agents to explore semantic knowledge graphs

Conversational agents, namely applications which allow users to communicate with machines through natural language, are becoming commonplace in many business and home environments. Technologies such as Google Home, Siri and Amazon Alexa present us with an easy way to access music, films, or plan our day. Many services, for example banking, have incorporated chatbots into existing processes to manage interactions with customers, including to direct them to the right information or department. This saves companies money and can save customers time waiting in a queue.

Typical applications for conversational agents tackle concise user tasks for mundane processes which can be translated to a finite set of user intentions. Here the risks of an incorrect or misleading response are low and the resulting consequences limited, particularly given the ease with which a user can validate results against an expected and desired conclusion to their interaction. Take the example of a user wishing to listen to a playlist of a specific music genre. They can task the conversational agent with finding and playing such a playlist. It does not necessarily matter to the user exactly how the agent has reasoned what music should be played in the playlist, what the track order should be, or many other aspects. The users intention is straightforward and the consequences of an unwanted track are limited i.e. the user will make an assessment of the track as soon as they hear it, at which point they may decide to skip the track, or ask for a different playlist. The result of the interaction therefore provides some information to the user which they can easily interpret, validate and make an appropriate, timely, response. If the user were repeatedly presented with the wrong genre of music, however, their need to understand the underlying algorithmic process and constraints will become more important.

We believe there is desire and benefit to using conversational agents for natural and shared human-machine reasoning in applications for which the interpretation of responses are high risk and high consequence, such as critical decision making environments.

IUI Workshops'19, March 20, 2019, Los Angeles, USA

However, there are significant differences between the requirements for this and typical conversational agents, which must be considered in design.

Consider the example where a user wishes to perform analysis of a certain entity and explore it's associations with another entity through a conversational agent. The agent can provide responses and a simple explanation. This interaction can be an example of shared reasoning, where the user is directing the conversation based upon their own thoughts and the agent is interpreting the user's intentions and objects of interest, before making inferences to extract data to include in it's response. There are dangers present where actions which are informed by shared reasoning are high risk and high consequence. For example, if through shared reasoning the user incorrectly confirms their hypothesis and directs a subsequent action, such as arresting an innocent person or launching an unnecessary offensive operation. Some specific risks include; the way the agent interprets subtleties in the intention of the user request, the introduction of bias, the way the agent explains a complex series of connections, the way it translates the uncertainty involved in those connections and exposes missing data, and the propagation of uncertainty along the conclusion pathway. Additionally, the algorithm selected by the agent to explore data influences which pathway is described, this needs explaining to a user. Errors in mitigating any of these risks could lead to a mistaken, or deliberately manipulated, action with adverse effects. Unlike typical conversational agent applications, the user does not necessarily have an expectation or an easy way to validate results. They also need to access, understand and interpret the evidence underpinning any response. A simple chat with summarised text responses cannot fully address the risks noted above and therefore lacks transparency and a mechanism that supports situation awareness, rigour, visible reasoning, and sense making. Wong et al. [41] present the 'Fluidity and Rigour Model' which helps explain the design requirements for applications which aim to mitigate these risks and aid the reasoning of intelligence analysts.

To date, research into conversational agents has looked to improve the agent itself, by making it human-like or its responses more contextual. This paper however considers the vulnerabilities of shared human-machine reasoning and the requirements for visibility of interactions, identifying key considerations. A framework is presented, with input from experienced military intelligence analysts, of foundational research areas for developing shared human-machine reasoning applications, such as conversational agents, for evidence based critical decision making environments.

In situations where a user aims to retrieve information or data, particularly if they do not already know how to access it or what they are looking for, a conversation can be the prefered way to reach their desired outcome. The conversational agent provides a gateway to the information they seek, extracting the users intentions through a two way dialogue, then translating these intentions into query language and describing the results back. For many users this is a far more intuitive approach to retrieve information [3] than a complex query, particularly if the query language is uncommon to them. We propose that a more intuitive interaction with data could also benefit the areas of sense making and intelligence analysis. Intelligence analysts require the ability to explore large volumes of multidimensional data in a way which feels natural given their skills and training. Current approaches to allow exploration of multidimensional data, however, are complex and inflexible, requiring chart or graph interactions which can feel unnatural and inconsistent to non-technical users. This inhibits the analyst's ability to derive underlying narratives and test their hypotheses. Additionally, common data visualisations such as chart dashboards do not clearly translate to some analysis methodologies which require the interpretation of conflicting hypotheses alongside uncertainty. As described by Wong et. al [41] "analysts need a kind of user interface that allows them to easily explore different ways to organise and sequence existing data into plausible stories or explanations that can eventually evolve into narratives that bind the data together into a formal explanation." Such exploration can be defined as 'storyboarding' where an analyst will attempt to draw together a plausible narrative, involving missing and uncertain data, where an analysts hypothesised connections also need representation. When conducting this type of analysis an audited, flexible, conversation with an agent could be beneficial.

There are a variety of approaches to developing conversational agents, however the neural models which power most of the commercially available smart assistants lack a sense of context and grounding which their human interlocutors possess [16]. Instead knowledge augmented models which make use of 'semantic knowledge graphs' may be the answer to provide more contextual, and meaningful, interactions. Semantic knowledge graphs are developing as an important approach to manage and store information and observations for use in intelligence analysis. An example of such an observation is a connection between a person and organisation i.e. "Person A works for Organisation C". By using knowledge graphs we are able to describe any type of information, with many properties and classes which algorithms can call upon when performing queries. This provides an analyst with the ability to ask powerful queries, such as semantic search, if they have a necessary understanding of the query syntax [11]. Semantic knowledge graphs allow for some automated reasoning to be performed and thus applications which use them can demonstrate shared human-machine reasoning.

Studies to date have focused upon the development of methods and technologies for conversational agents to deliver believable and contextual conversations. While potentially extremely helpful, this paper proposes that the use of conversational agents to interpret intelligence observations through semantic knowledge graphs can introduce risks due to a loss of situational awareness (SA). SA plays a vital role in dynamic decision making environments [43] such as intelligence analysis. For military or police commanders to make the best possible decisions in complex and uncertain environments they need to maximise their SA by making optimum use of available knowledge. By introducing a conversational agent to parse queries, traverse the graph with an appropriate algorithm or set of algorithms and describe results, all as decided by the agent, a layer of abstraction is introduced which masks true SA. The process which interprets a users query before returning a response can be described in this way as a 'black box', as identified as a key issue in research in the area of machine learning and neural networks [4]. While it is theoretically possible to explain the algorithm which is chosen, and each of the steps according to semantic reasoning, this process is not visible to a user through a conversational interface. To allow for evidence based sense making, conversational interfaces must, therefore, be designed to provide visibility of large and complex reasoning paths and the surrounding contexts. It must also be possible for analysts who are not expert statisticians or data scientists to understand interactions, perhaps making use of accompanying visual aids.

1.2 Research Contribution

We propose that there are some critical vulnerabilities in the field of intelligence analysis and other evidence based decision making environments. These are magnified by the use of applications which share reasoning ability between both human and machine, such as conversational agents.

Research is required to reach an understanding of how machine reasoning can be introduced alongside human reasoning in a way which mitigates vulnerabilities, whilst still exploiting the significant benefits of more natural and powerful interactions between humans and data. This paper delivers a framework for providing algorithmic transparency, with associated research areas which are the foundation to exploring how applications can be designed to deliver shared human-machine reasoning. We examine the example of conversational agents used in conjunction with semantic knowledge graphs. The research is specifically tailored to an evidence based decision making scenario (intelligence analysis) informed by semi-structured interviews with analysts who have experience working in intelligence environments. The framework helps segment key considerations and vulnerabilities for agent design and identifies challenges and areas for further research.

2 RELATED WORK

The framework proposed in this paper links various research topics which are each significant in their own right. We take a broad look at previous work on one example of an application technology which provides shared human-machine reasoning, that of conversational agents for querying semantic knowledge graphs. There are important aspects of our framework which have not received attention in research to date, specifically an understanding of how to make machine reasoning more visible to a user when intertwined with human reasoning. This is crucial when agents are used in decision making environments and is a central question for our research.

2.1 Development of Conversational Agents

The desire for humans to be able to speak with machines through human-like language has been around for some time, with relevant research published as early as the 1950's [33]. Important advances in technology over the past few decades, in particular the development of the internet as a source for knowledge, have led to rapid increases in conversational agent capabilities [6] with accompanying research publications. The focus of research to date has been on improving an agents conversational abilities including their understanding of a user's meaning and the flow of the conversation.

Early chat interfaces, notably ELIZA [37] and ALICE (Artificial Linguistic Internet Computer Entity), were built with the aim of deceiving humans into believing they were interacting with another human by providing human-like responses. While work towards these early bots focused on the ability of a machine to be able to imitate a human, for the purposes of this paper we are interested in conversational agents which can be used to aid intelligence analysts to perform reasoning, and we will therefore apply the definition of 'spoken dialogue systems' given by McTear [18] to describe the type of conversational agents relevant to our research. These are defined as computer systems that use spoken language to interact with users to accomplish a task. The potential uses for task based conversational agents is extremely broad. Examples include 'Anna', who was introduced by IKEA in the mid 2000's and developed with personification, and CHARLIE. In Anna's case, the task was to direct IKEA customers towards products they may be interested in buying. CHARLIE is a chat bot to assist students, for example by allowing them to find information about tests [19]. Students can ask CHARLIE for a complete test, for a personalised test (choosing the number of questions), and ask 'free questions' which are not part of any particular test. These two examples of task based conversational agents have commonality in that they are low risk; other than annoying the user, an incorrect response does not lead to catastrophe. Additionally, errors are quickly identifiable with little uncertainty. An IKEA customer has a clearly defined goal for their task when they communicate with Anna, and they will know when their task has been completed. Likewise, a student will recognise if CHARLIE is asking questions which are not on their syllabus. The consequences to incorrect or misleading responses from either Anna or CHARLIE will therefore be limited.

One area where conversational agents have been applied to higher risk and more uncertain environments is in health care. It is dangerous in decision making environments if a conversational agent is able to bias a decision, or influence the decision maker. Robertson et al. [26] evaluate a chat application, built in their case as an aid for diagnosing prostate cancer, and found that using the app helped to "take fear out of decision making". Without complete visibility of how an application had guided a user to the decision, including the background processes beneath the thinking, conversational agents demonstrate serious risk of manipulating a decision maker. Another example where this is potentially a problem is in chat interfaces which provide news stories, such as the NBC Politics Bot which was launched prior to the 2016 US Presidential election. How can we be sure the bot is not biased, particularly if it has been trained using selected data and machine learning approaches [17], or that the bot is not choosing an adverse path or filter to access and describe information to a user? To date, to the knowledge of the authors of this paper, there has not been research to understand how and when we should shed light on the thinking of a conversational agent alongside agent responses. Laranjo et al. [14] find that the use of conversational agents in health care includes a mixture of finite-state (where there are predetermined steps), frame-based (where questions are based upon a template), and agent-based (where communication depends on the reasoning of human and agent). We are interested in agent-based conversational agents as these demonstrate shared human-machine reasoning. Agent-based applications include Siri, Allo, Alexa and Cortana, referenced by Mathur and Singh [16]. Significant concerns have been identified with these types of agent, for example by Miner et al. [20] that "when asked simple questions about mental health, interpersonal violence, and physical health, Siri, Google Now, Cortana, and S Voice responded inconsistently and incompletely." To be used in high risk and high consequence decision making environments where responses cannot be easily verified, conversational agents must provide visibility of their thinking and justifications through the underlying data or evidence. Laranjo et al. [14] recognise the risk that comes with applying conversational agents in high risk scenarios, including "privacy breaches, technical problems, problematic responses, or patient harm."

The issues of capturing context, managing inconsistency in responses, providing trust and confidence, and removing bias informed by training data, can be mitigated if we provide the agent with a foundation for knowledge from which it can extract meaning and content deterministically. This is the case if we allow the conversational agent to interact with a semantic knowledge graph to perform specific search and reasoning tasks.

2.2 Making inferences with semantic knowledge graphs

Hoppe et al. [11] do not define an application as semantic due to a particular technology used, rather they consider a "semantic application as one where semantics (i. e., the meaning of domain terminology) are explicitly or implicitly utilized in order to improve the usability of the application." We apply this same definition. Semantic knowledge graphs provide a user with the power to perform queries and retrieve data which incorporates a level of inferencing about the users query. Hoppe et al. [11] provide a classic example of "semantic search", compared to a simple keyword search. Instead of searching for information which matches the keyword we can search based upon a concept, or class, of an instance in the knowledge graph. If I use a conversational agent underpinned by a knowledge graph I can ask more complex queries related both to classes and instances, for example, 'what "organisations" (semantic class) is the person "Poppy" (instance) linked to?' Due to the semantic nature of the graph I can identify all instances of organisation and find connections across the graph to the target. The agent can infer relevant entities, and any other sub-classes of entity or contextual information, through the semantic class I have provided. Additionally rule based reasoning can be applied. In this way a conversational agent using a knowledge graph can be defined as an agent-based model, where reasoning is shared between human and machine in a conversation.

Semantic knowledge graphs can be complex to query, particularly with more advanced graph traversal and query methods. To query an RDF graph, for example, we can use the SPARQL query language [23]. Additionally we can use SPARQL Inferencing Notation (SPIN), for example to work out the value of a property based on other properties in a graph. Figure 1 shows an example SPARQL query [23]. This syntax, even for a relatively simple query, can appear complex to novice users. A conversational interface provides a route to explore large knowledge graphs through natural language without the need to write any query syntax.

Figure 1: Example SPARQL Query Syntax

```
PREFIX mo: <http://purl.org/ontology/mo/>
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
SELECT ?name ?img ?hp ?loc
WHERE {
        ?a a mo:MusicArtist ;
        foaf:name ?name .
        OPTIONAL { ?a foaf:img ?img }
        OPTIONAL { ?a foaf:homepage ?hp }
        OPTIONAL { ?a foaf:based_near ?loc }
}
```

The power of semantic knowledge graphs has led them to become crucial to supporting many AI applications, including question and answer systems [29, 35]. Willemsen presents the use of knowledge graphs as the foundation to a conversational agent [39] and also provides good reasons for doing so. Using a knowledge graph to explore entities extracted in a users input text allows for a more contextual understanding of what the user requires, as well as the opportunity to provide added value to their request. The architecture of conversational agents described by Willemsen [40] includes aspects such as a domain model (ontology), a text understanding layer (natural language processing), a knowledge graph layer which is built from the previous two layers, and a user context layer. The user context layer is focused on conversational abilities such as staying in context, keeping track of the conversation flow, and relating the conversation to entry points in the knowledge graph. Willemsen [40] demonstrates a simple search for a specific type of directed relationship for a single entity. A user is unlikely to require significant additional explanation in this scenario, however if we consider a decision making environment, such as intelligence analysis, it becomes more complicated. Even with a concise and clearly articulated search, such as "who does person x work for?", there are additional factors which an analyst would want to understand beyond a simple text response. In intelligence analysis the provenance of the information is important, as is the reliability or confidence given to it. There are cases where missing links are inferred in knowledge graphs [5], machine learning has produced edges (observations or connections) within the knowledge graph [21], or SPIN rules have inferred links [1, 32], so the explanation of these to an analyst also needs consideration. Additionally, more complex queries will require some graph traversal for which the choice of traversal algorithm is crucial to determine what information is described to an analyst in the agents text response. A choice of Dijkstra's single shortest path, for example, would identify different information to an alternative heuristic method for finding multiple paths between two nodes. Sorokin and Gurevych [27] describe a method for not only extracting entities and relations from a users query, but also the structure of their query and their underlying intention. The structure has implications for the results which will be returned, particularly when directional relationships exist. While it is important that the machine can understand the user's query and intention, it is also critical that the user can verify this.

Conversational interfaces require the ability to identify a users intention and intention definition is therefore an important consideration, as these will trigger the relevant action in response to a query. Intentions may be domain specific, for example an intelligence analyst may wish to perform particular tasks which do not translate to other environments. To identify possible tasks we may look to use existing work, such as the task taxonomy for graph visualisation presented by Lee et al. [15], to understand generic queries a user may wish to make. There has been work to provide advice and solutions to the visualisation of large scale knowledge graphs [28], and to provide situational awareness of graphs for intelligence analysis [9], which could be a starting point for visualisating a conversational agents thought process. However, to date the use of conversational agents for intelligence analysis and the various vulnerabilities which are introduced, in addition to potential mitigation's through user interface design and visualisation, have not received attention. We believe that decision making environments have additional requirements for visibility beyond traditional applications for conversational agents, which have not been considered in existing research. We can understand these requirements better with a look to research in the area of intelligence analysis and sense making.

2.3 Intelligence Analysis Methods and Requirements

Intelligence analysts are crucial to military decision making because they provide situational awareness (SA) to commanders. A key method applied by military analysts is situational logic, this underpins much of an analysts standard process to achieve an understanding of a situation. Heuer [10] provides a description of the situational logic approach, that "starting with the known facts of the current situation and an understanding of the unique forces at work at that particular time and place, the analyst seeks to identify the logical antecedents or consequences of the situation. A scenario is developed that hangs together as a plausible narrative. The analyst may work backwards to explain the origins or causes of the current situation or forward to estimate the future outcome." A traditional approach to perform situational logic analysis is 'Analysis of Competing Hypotheses' (ACH), developed by Heuer almost 50 years ago. ACH is a matrix approach which provides rigour when comparing evidence against different hypotheses, and whilst it may not always be applied in it's entirety by military analysts, aspects of ACH are commonly used.

Looking to ACH allows us to understand critical aspects which feature in an analysts thinking. Such as, the evidence which underpins hypotheses and the related strengths and weaknesses, the propagation of weaknesses in a fused evidence picture, the ability to compare the strength of multiple alternative hypotheses, the relative impact of removing pieces of evidence upon hypotheses, and the relative influence of different hypotheses and evidence upon possible narratives.

While the principles of ACH are sound, in practice it is flawed. ACH is typically a matrix table approach and the table display itself is limited in the amount of information which can be clearly articulated, so the text is summarised and lacking in surrounding context. Additionally, it introduces an arbitrary structure to hypotheses and evidence. This can produce adverse cognitive effects where the way, and order, in which hypotheses are listed can affect how much they are considered. Additionally, if analysts rely on their experience alone when assessing possible hypotheses they are prone to bias. "Psychological research into how people go about generating hypotheses shows that people are actually rather poor at thinking of all the possibilities. If a person does not even generate the correct hypothesis for consideration, obviously he or she will not get the correct answer."[10]

As Wong and Varga [42] explain, performing situational logic analysis to identify and test hypotheses is not straightforward. An analyst starts with a fairly ill-defined query, likely based upon their own experience, then follows an iterative process querying, assessing, learning, drawing conclusions, making judgments and generating explanations to direct further searches. They will likely amend existing hypotheses or come up with new ideas throughout this process. Wong et al. [41] present the 'Fluidity and Rigour' model, this model demonstrates the wide variety of shifting reasoning strategies applied by analysts. These range from 'leap of faith' observations and storytelling, with unknown and uncertain data, to rigourous and systematic evaluations of hypotheses, such as applied in ACH. Conversational agents allow for fluidity, where they can support wide variability in thinking. They can also support rigour, where results are valid and underpinned by evidence, if the underlying thinking and machine reasoning of the agent can be demonstrated to an analyst. Conversational agents can therefore be used to aid reasoning, however, whilst in traditional visual analytics the focus is on making these processes visible, using a conversational agent alone to perform these tasks can mask the underlying methods and data. This information needs to be visible to satisfy the requirement for rigour.

In time sensitive scenarios, for example if an analyst is tasked to understand a situation prior to an imminent military action with little lead time, situational awareness is particularly important. Thomas and Cook [30] identify situational awareness as the perception of the elements in the environment within a volume of space and time; comprehension of their meaning; the projection of their status into the near future; and the prediction of how various actions will affect the fulfillment of one's goals. A thorough situational logic analysis can achieve perception of elements (known facts), and can hang them together as a plausible narrative which involves comprehension of their meaning and projection of possible future developments. However, we believe that a traditional methodology such as ACH is flawed and would typically take too long to complete satisfactorily. Instead, we propose that conversational agents and semantic knowledge graphs lend themselves well to situational logic analysis, where 'known' facts can be captured as observations, along with the confidence, timestamp and provenance of those observations. The graph can then be appended with hypothesised associations as additional observations. In this way storyboards for a scenario can be captured within the graph. We can utilise inferencing capabilities and graph algorithms to piece together information (which may be outside our own personal awareness and experience) and refute hypotheses. This is an example of shared human-machine reasoning, where a human is able to deliver more intuitive reasoning, with a focus on abduction and induction, including 'leap of faith' ideas, while the machine can augment human reasoning with deduction and induction by formal argument, scientific rigour and evidence.

While traditional interfaces to provide this are complex and lack fluidity, a natural language approach to interactions could be the solution. An analyst can easily interact in natural language with a conversational agent, in a timely fashion, to explore the graph before concluding with a plausible narrative and achieving SA much more quickly. Crucial to providing true SA, however, is that an analyst can easily and visibly understand how and why a conversational agent has provided the responses they have. In a sense, this requires visualisation of the agents conclusion pathway. To date, as far as we are aware, there has not been research conducted to understand the vulnerabilities to introducing conversational agents in the field of intelligence analysis, nor design steps which could help mitigate risks.

3 FRAMEWORK

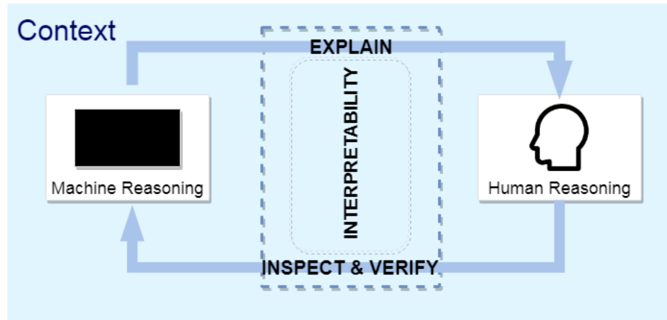
We have produced a research framework to identify the design requirements for applications which involve shared human-machine reasoning for use in decision making fields, such as intelligence analysis. The framework is underpinned by an exploration of existing literature and unstructured interviews with a small selection of experienced military intelligence analysts. We provide an example aid to help demonstrate the 'visibility' aspect of the framework.

Approaches to date which develop machine reasoning through conversational agents, including [27, 29, 40], focus upon data extraction coupled with language processing and contextualisation, to provide better understanding of a user's query and more informed responses from an agent. These are important areas of research for providing the underpinning technologies which enable shared reasoning with conversational agents. However, design aspects for agents used for critical decision making have not received significant attention in research. Figure 2 presents a framework for designing applications which involve shared human-machine reasoning, such as conversational agents for knowledge exploration.

The framework diagram presents the relationship between machine reasoning, shown as a 'black box', and human reasoning. There has been much work and discussion describing machine learning methods as a 'black box'[4], and the associated vulnerabilities of this [22]. In a similar way a conversational agent's exploration of a complex and large knowledge graph can be a 'black box' if there is too much information to explain clearly. An interface needs to provide 'explainability' and 'visibility' (the ability to inspect and verify) in order to share cognition between machine and human, within the context of a given environment, task and user. This framework can be used to inform the design requirements for such interfaces and to identify critical areas for future research.

The human user requires explainability of the cognition taking place within a 'black box' (XAI). XAI has received a large amount of attention in recent years, with a focus upon understanding machine learning classifications. The meaning of explainability is key to how it is designed into interfaces. Current XAI research, as reviewed by Gilpin et al. [8], gives the definition that XAI is a combination of interpretability and completeness, where interpretability is linked to explaining the internals of a system and completeness is to describe it as accurately as possible. To date this angle of explainability has looked to express the process within the mathematical model, for example how to represent important features which are influencing a deep neural network. There are numerous tools which have been used to explain a classification, for example Lime [25]. For a discrete

Figure 2: Algorithmic Transparency Framework



Algorithmic Transparency Framework: What the user needs from black box algorithms: (i) explanations of how results from algorithms are arrived at (ii) explanations that are interpretable by the user in a manner that makes sense to them (e.g. the internals of the algorithm, including important features, an indication of accuracy or confidence, and an understanding of the data used and uncertainties, all presented in a manner which enables the user to assess if the results are sensible), (iii) visibility of the functional relationships mapped against the goals and constraints of the system, and (iv) context in which to interpret the explanations. NB: by showing goals and constraints, we include some key elements of context, e.g. goals include some notion of the priorities and therefore some understanding of the problem, hence the context.

classification we can use Lime to visibly represent the feature results which the machine learning algorithm has picked as particularly relevant to a given classification.

For applications which allow fluidity and rigour in shared human-machine reasoning, it is not enough to merely provide explainability of the internal workings of a system through result metrics. There needs to also be visibility of what reasoning the machine is doing and why, how it's reasoning fits within the fluidity and rigour model [41], and the ability to examine conclusion pathways and the effects of alternative reasoning strategies, within the context of the goals and constraints of the system. Visibility requires an appreciation of the uncertainties and gaps in available data and must allow a user to understand the influence and justifications of machine reasoning within their own reasoning and analysis. The concept of visibility has not been addressed in previous research in this area.

This paper presents a simple scenario to demonstrate how the visibility of machine reasoning can be designed within an application alongside human reasoning. The example considers a conversational agent query system for a semantic knowledge graph.

3.1 Example: Conversational agents for graph exploration

3.1.1 Analyst Interviews. In order to understand what requirements exist for visibility of machine reasoning in conversational agent responses, and to map functional relationships against the goals and constraints, we first need to understand what visibility means in the context of intelligence analysis. Much work has been done to understand the general thought processes applied by analysts, however to date research has not considered the interaction between an analyst and conversational agent and the impact of shared reasoning. We begin this discussion by conducting interviews with a small number of experienced intelligence analysts, to understand for what tasks conversational agents could help, any vulnerabilities which exist, and for each task what visibility means to an analyst.

The analysts interviewed for this study identified areas where a natural language interaction with data could be extremely beneficial. For example, when performing situational logic analysis analysts apply a process of hypothesis creation, testing, and comparison, related to real world entities. Analysts formulate hypotheses, often linked to future strategy, impact, events, and activities i.e. 'that Person X and Person Y are travelling to Location C for Event A, which will have impact Z'. A key requirement is to understand the connections between these entities and the surrounding context, in particular related to the key points of connection. Considerations need to take into account the provenance and certainty of observations and the impact of data changes, including unexpected observations, upon the analysts hypothesis. For example, if by accounting for uncertain data an alternative hypothesis presents itself as most likely, or if additional data is included after an update in the situation which changes the overall picture.

A semantic knowledge graph approach can provide much needed persistence of data, with rigour in the capture of contextual information. However, a graph increases in complexity and scale as it evolves over time and it becomes increasingly difficult for an analyst to assess their hypotheses against it. The analysts interviewed in this study identified that current analytics tools to explore graph data are often over-complicated, with significant learning required to understand how to perform functional interactions for filtering and configuration. Resulting visualisations are then overloaded with too much information. Additionally, there is insufficient explanation of the meaning and constraints of functionality where analysts are interested in "function rather than mechanics". This leads to a barrier to analysts using tools because they find them off-putting and unnatural. A conversational approach could provide access to powerful functionality, but with less complication and learning required, and greater understanding of methods through two way dialogue. This can help an analyst to explain difficult concepts, such as their level of risk aversion when considering appropriate evidence across a conclusion pathway.

Analysts identified a number of other benefits to using conversational agents, beyond being more natural to interact with. When exploring data they can allow for timely, coherent, and regular searches, where an ongoing conversation is maintained and the agents memory can be accessed and utilised. This capability would be useful for analysts who want to ask questions such as, "have there been any more visits to Location X?". A key feature of conversational agents, identified by the analysts, is the ability to clearly articulate an audit trail to explain how information was found in the process of an investigation. This trail helps provide ethical accountability. Each interaction with the agent provides a time-stamped message, including associated information found and the state of the graph data at that point in time. Analysts can be influenced by bias and by capturing their line of questioning an agent could aid an analyst to consider alternative possibilities. A conversational agent can allow for a deeper explanation of findings, including feedback and suggestions for selected alternative inquiries which is based upon a knowledge of the underlying and surrounding data. To provide a raw picture of all this data to an analyst would be too voluminous and complex for them to digest manually. In this way an agent can aid an analyst to identify alternative hypotheses which are not restricted to their own experiences or assumptions.

This reasoning aspect of conversational agents goes beyond a simple query tool, to incorporate elements of sense making and inferencing, and there are vulnerabilities to doing so. Analysts identified several risks when using conversational agents. These represent important problems which require mitigation to confidently apply conversational agents in the area of intelligence analysis. If an agent is able to guide an analyst by refuting and suggesting alternative hypotheses then there is potential for the analyst to be mislead. An agent could guide an analyst towards inaccurate conclusions in a way which is difficult for the analyst to refute, given the complexity of the underlying graph and the fact that it is not visible to the analyst. If an analyst is interested in key connections in a path they are vulnerable to the agents choice of path, where there is an adverse impact if non-relevant connections are identified as key. Within the conversation text itself it is difficult to describe the provenance and certainty of information as well as the key information, particularly for many connecting observations. This leads to textual responses which are either hard to interpret and overload the analyst with too much information, or are summarised so that important information can be missing.

To help mitigate some of these issues the analysts interviewed described what requirements for visibility in conversational agents they have, in association with their goals for a system. Analysts felt an understanding of the underlying processes and algorithms applied by conversational agents should focus upon the functional meaning, in light of the intelligence analysis task, rather than any mathematical method. Specifically, analysts were interested in 'how' and 'where' a conversational agent was exploring the graph and 'why' it deemed information to be interesting, including the specifics of the sub-graph extracted, such as the provenance, history and confidence of observations. Analysts emphasised the need for a balance between identifying the 'key' underlying data observations or entities, while not overwhelming the user, and also providing a contextual understanding of what 'key' means. Analysts were particularly interested in allowing for human reasoning of more intangible observations, alongside the deductive rigour of the machine. This would include an understanding of weaknesses, missing data, and ability to apply intuition. Additionally, visibility of past conversations, the current state of the conversation, and the state and evolution of the graph at each stage, is important for auditing purposes and ethical accountability.

3.1.2 Example Case: Scenario. A conversational agent's interpretation of a user's intention will inform which thought process, or algorithm, is applied to deliver a response. For example, a user's query to find relationships between two different entities may invoke a 'find connections' intention. This approach to match query to intention is typically performed using machine learning techniques for classification. Accurate conversational responses therefore begin with an assessment of possible intentions and an accurate machine learning intention classifier, and later involve the accuracy of entity and relationship extraction, the building of knowledge graph query syntax, subjectivity in which algorithms meet which intentions, variability and constraints of heuristic methods, and the reliability and completeness of the knowledge graph itself. There are, therefore, uncertainties which need to be addressed within a user interface. For example, what is the impact upon an analysts decision if an agent interprets a subtly different intention, with different goals and constraints, and employs a different algorithm? How many intentions should an agent allow? How distinct do they need to be to mitigate uncertainties? Fundamentally we need to understand how 'visibility' of agent thinking can be provided to an analyst.

In intelligence analysis it is crucially important that analysts can fully interpret the information and evidence which is guiding their decisions. Without visibility of their 'conclusion pathway', i.e. the pieces of information which are informing their acceptance or rejection of hypotheses, they are vulnerable to mistakes, personal and experiential bias, and deception. The use of conversational agents presents challenges to the visibility of thought processes, by handing over some of this processing to an agent. The nature of chat bot interfaces, where a user types a message and receives a text reply can encourage a narrow focus for investigation. A user will typically receive responses based upon their questions, with little awareness of data observations which lie on the periphery of their line of questioning (reduced SA). The bigger picture is hidden and opportunities for deception are increased.

Potential vulnerabilities are best explained with an example, as described in Table 1. All of these queries relate to a straightforward 'connections' intent which finds a path between pairs of entities. We are provided with information akin to 'explainability' in the Algorithmic Transparency Framework (Figure 2), where the internals of the system (the graph connections which are found between our entities of interest) are described in natural language.

Scenario: An information request is received by an analyst to understand the supply of equipment and ingredients to produce a weapon ('X') to 'Organisation X'. It is suspected that an individual with access to the necessary equipment (a scientist) is supplying the goods.

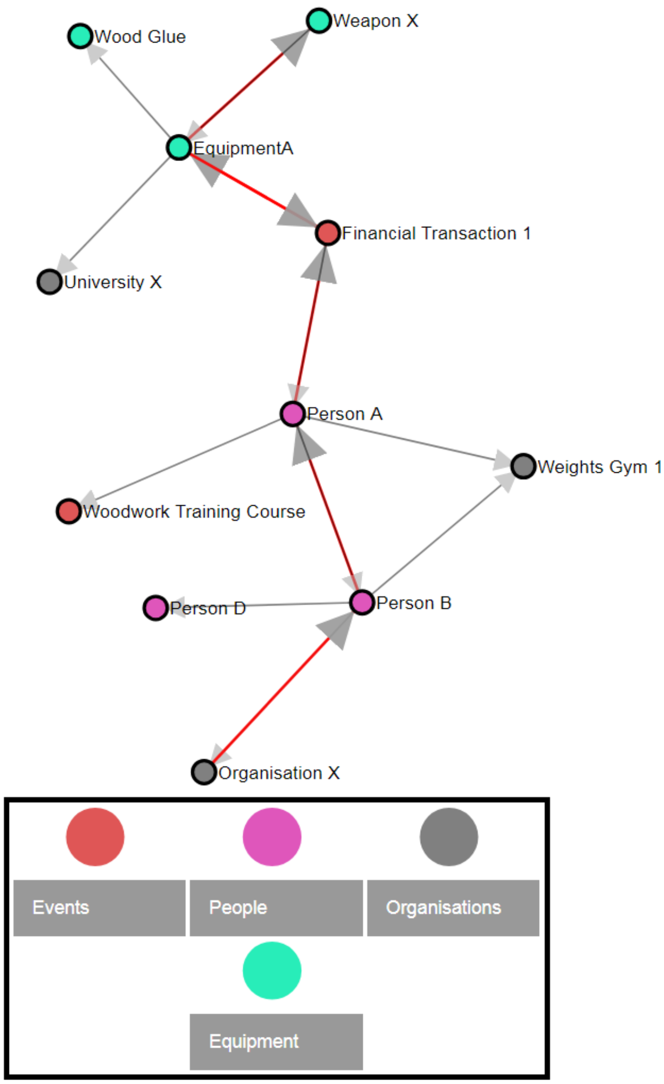
Table 1: Example Conversational Agent Transcript

Stage	Agent	Text Entry
1	Human	Is there a connection between Organisation X and any scientists?
2	Machine	Yes, Person B is a member of Organisation X. Person B knows Person A. Person A is a scientist.
3	Human	Is Person A linked to weapon X?
4	Machine	Yes. Equipment A is used to produce weapon X, Financial Transaction 1 purchased Equipment A, Person A participated in Financial Transaction 1.

The conversational agent has identified that Person A is a scientist. It has also identified that Person A is connected to Organisation X, therefore the agent can perform deductive reasoning to find that Organisation X is linked to a scientist. Furthermore, Person A appears a good candidate to suspect in supplying Organisation X with weapon X. We can see that Person A is connected to both organisation and weapon, and we have an explanation for how. However, any uncertainty or alternative narratives within the data are not presented to us and the response is narrowly framed by our line of questioning. There is a lot more information needed by an analyst in order to understand these connections. This is because the explanation does not take into account the requirements for 'visibility', including how the conversational agent maps it's reasoning to the analyst's goal, or an understanding of the constraints present in the reasoning approach. In this case, the analyst wishes to test their hypothesis and to allow for reasoning about alternative possibilities. The system, however, is constrained to apply a single shortest path algorithm which traverses the graph and returns data to the analyst. Observations which lie on longer paths are ignored and an analysts true situational awareness is reduced. Even worse, data can be introduced to mislead an algorithm, and thus manipulate the results presented to a user. This vulnerability ties closely with confirmation bias, where by understanding how the algorithm will look across data points it may be possible to introduce data to reinforce bias.

This is a simplistic example, but it helps demonstrate some of the pitfalls with chat bots and data filtering algorithms which reduce situational awareness. This is particularly the case in more realistic scenarios or if advanced graph traversal algorithms such as probabilistic methods, heuristic approaches to explore multiple paths, or pattern matching methods are applied. As a situation becomes more complex, for example with observations which arise from different sources and demonstrate varying levels of confidence and reliability, designing for visibility of machine reasoning becomes critical to providing a clear picture which empowers an analyst to perform human reasoning. Much research has looked to develop explainability of machine learning algorithms which present the user with mathematical representations, for example, of how features in the model relate to classification results. Little has been done, however, to understand how visibility should be provided for these

Figure 3: Example Visual Aid for Conversational Agent



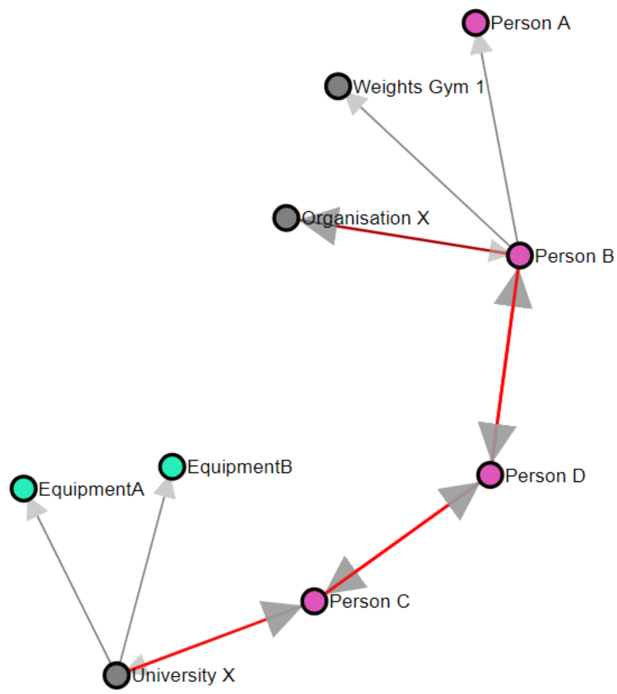
models within the context of their use, nor for how knowledge graph traversal algorithms are applied and explained to a user in tandem with conversational agents. These are key areas requiring further work.

3.1.3 Example Case: Visibility. The example visual aid shown in Figure 3 revisits the scenario described earlier in Table 1 and accompanies the textual responses. Figure 3 displays the path found by the agent in addition to other nodes which are close by (within a single edge from the path). There is a key for the colour of nodes provided in the interface which is linked to their semantic class. The path found is akin to the agents conclusion pathway as this traces the series of observations which connect the two entities of interest. The extra relationships which are not on the path provide additional context and better mapping between the algorithm functions and analyst goals for the system. By providing this addition to supplement the text in the visual form of a sub-graph network, analysts can better understand the conclusion pathway taken by the agent and this gives them greater visibility of the context in which deductions are made by the agent. For example, the agent has deduced that Organisation X is linked to a scientist, Person A, through Person B. However, this deduction ignores other possibilities for a relationship between Person A and Person B which do not involve Organisation X, for example membership at the same gym. Additionally, the agent's reasoning does not consider other entities which have similar access to equipment as scientists, for example university students. An analyst, when faced with this graph, could perform more intuitive abductive reasoning to question the role of the university. The systems constraints are more obvious, where an analyst can identify paths which have not been explored and nodes which could be relevant but have been missed. Without visibility of the machine thought processes, the human cannot interpret, critique, nor build upon machine reasoning.

The additional visual aid is helpful for an analyst to sense check the agents thinking, providing some ability to verify findings by comparing alternative hypotheses which may arise from the inclusion of close nodes. Take the first query, for example, where the agent finds a connection between Organisation X and a scientist (Person A). The agent can explain that the most critical node in the path is Person B and an analyst therefore must be confident in the association between Person A and Person B to be confident in the path as a whole. By considering the surrounding context we see that both people are members of the same weights gym. There is a plausible association which is not related to Organisation X. Likewise, if we take a look at the most critical node linking Person A to Weapon X, which is Equipment A. Person A has purchased Equipment A which is used to produce Weapon X, however it is also used to produce Wood Glue and Person A has participated in a woodwork training course. Again, they have a plausible reason for making this purchase which is not related to Weapon X and the conversational agent has ignored this.

The graph in Figure 3 provides the additional context that Equipment A is also owned by University X. If an analyst explores this connection they will see the display shown in Figure 4. Figure 4 shows just the sub-graph for the agents response to "is there a path between University X and Organisation X?". We find that there is indeed and again Person B is the most critical node, Person D and Person C (a student at the university) are also important. The addition of the visual aid to the conversational responses helps to overcome some of the issues identified by analysts, specifically by providing visibility of the conclusion pathway, additional context and algorithm constraints, and by highlighting key points of connection within the graph. The conversation text itself can also pull out key vulnerabilities, for example where a node is particularly important to a path based upon its betweenness centrality score [7]. Betweenness centrality finds key bridging nodes between sub-graphs. We have therefore deemed these nodes will have the largest impact upon the conclusion path if they are removed and the analyst needs to be confident in their accuracy and associated connections.

Figure 4: Example Visual Aid with Further Exploration



4 FUTURE WORK

The example visual aid is a helpful start, however it is flawed in many ways. An important issue facing analysts is information overload. In the simple example provided it is easy for an analyst to understand the graph visualisation, however in a more realistic scenario the complexity and scale of the graph would present a significant challenge. To tackle this problem more advanced traversal algorithms are required in addition to utilising the reasoning power of semantic knowledge graphs. Approaches such as concept lattice analysis [38] could also be explored to allow for greater complexity in the concepts and associated sub-concepts expressed by a conversational agent.

A more realistic scenario would require a smarter extraction of the surrounding graph context beyond that shown here, including uncertainties in the data and better definition of what we mean by 'close' to the path. Rather than simply displaying additional connections along a conclusion pathway, we need a method to display the important alternative connections which if considered could affect our hypotheses. To do this requires an understanding of how analysts make inferences across graphs. Wong and Varga [42] describe the concept of 'brown worms' to supplement argumentation which could be helpful to apply here. If an agent interprets a users query for connections as a hypothesis claim i.e. that the two entities are connected in a particular way, it can then extract a users grounds to the claim then trace through graph observations collecting evidence against those grounds. Using the brown worms concept, the conversational agent could describe important paths to the user and demonstrate how removing pieces of information which have lower reliability and confidence affects the evidence, grounds, and ultimately the claim. The definition of possible intentions which can be understood by the conversational agent and the subsequent methods they invoke is a key area for future development, as is an analysis of graph tasks and methods to visualise large scale data within and alongside conversational responses.

A greater understanding is needed of what 'visibility' means in the context of intelligence analysis tasks, goals and constraints, therefore more detailed studies should look to explore this concept with analysts.

The framework proposed in this paper has wider implications for the design of shared human-machine reasoning applications beyond the conversational agent example discussed. Future work should therefore also look to see how this framework can be applied to the design of other applications which provide shared human-machine reasoning, for example applications which include reasoning through machine learning.

5 CONCLUSION

There is a place for conversational agents in the field of intelligence analysis and, if designed carefully, they could deliver significant advantages to analysts compared to current practices and analytics tools. There are, however, risks to using them in a decision making environment where visibility of the reasoning, evidence, goals and constraints which underpin analysis is crucial, in addition to the explainability of a result. We provide a design framework which highlights important research areas to explore when looking to develop applications for shared human-machine reasoning, in fields which require evidence based decision making. Future work should look to apply the 'Algorithmic Transparency Framework' to the design of applications in real world scenarios and to tackle the challenges identified in this paper.

6 ACKNOWLEDGEMENTS

This research was assisted by experienced military intelligence analysts who work for the Defence Science Technology Laboratory (Dstl).

REFERENCES

[1] [n. d.]. SPIN (SPARQL Inferencing Notation).
[2] Agnese Augello, Mario Scriminaci, Salvatore Gaglio, and Giovanni Pilato. 2011. A Modular Framework for Versatile Conversational Agent Building. , 577-582 pages.
[3] Francois Bouchet and Jean-Paul Sansonnet. 2009. Subjectivity and Cognitive Biases Modeling for a Realistic and Efficient Assisting Conversational Agent. , 209-216 pages.
[4] Davide Castelvecchi. 2016. Can we open the black box of AI? *Nature* 538, 7623 (2016), 20.
[5] Wenhu Chen, Wenhan Xiong, Xifeng Yan, and William Wang. 2018. Variational Knowledge Graph Reasoning.
[6] Robert Epstein. 2009. *Parsing the Turing Test Philosophical and Methodological Issues in the Quest for the Thinking Computer* (1. ed.). Springer Netherlands, Dordrecht.
[7] Linton C. Freeman. 1977. A set of measures of centrality based on betweenness. *Sociometry* (1977), 35–41.
[8] Leilani H. Gilpin, David Bau, Ben Z. Yuan, Ayesha Bajwa, Michael Specter, and Lalana Kagal. 2018. Explaining Explanations: An Approach to Evaluating Interpretability of Machine Learning.
[9] Geoff Gross, Rakesh Nagi, and Kedar Sambhoos. 2014. A fuzzy graph matching approach in intelligence analysis and maintenance of continuous situational awareness. *Information Fusion* 18, 1 (2014), 43–61.

[10] Richards J. Heuer. 1999. *Psychology of intelligence analysis.*
[11] Thomas Hoppe, Bernhard Humm, Ulrich Schade, Timm Heuss, Matthias Hemmje, Tobias Vogel, and Benjamin Gernhardt. 2016. Corporate Semantic Web âĂŞ Applications, Technology, Methodology. *Informatik-Spektrum* 39, 1 (/02/01 2016), 57–63.
[12] T. Jankun-Kelly, Tim Dwyer, Danny Holten, Christophe Hurter, Martin Nollenburg, Chris Weaver, and Kai Xu. 2014. *Scalability considerations for multivariate graph visualization.* Springer International Publishing.
[13] Lorenz Klopfenstein, Saverio Delpriori, Silvia Malatini, and Alessandro Bogliolo. 2017. The Rise of Bots: A Survey of Conversational Interfaces, Patterns, and Paradigms. , 555-565 pages.
[14] Liliana Laranjo, Adam G. Dunn, Huong Ly Tong, Ahmet Baki Kocaballi, Jessica Chen, Rabia Bashir, Didi Surian, Blanca Gallego, Farah Magrabi, Annie Y. S. Lau, and Enrico Coiera. 2018. Conversational agents in healthcare: a systematic review. *Journal of the American Medical Informatics Association* 25, 9 (/09/01 2018), 1248–1258.
[15] Bongshin Lee, Catherine Plaisant, Cynthia Parr, Jean-Daniel Fekete, and Nathalie Henry. May 23, 2006. Task taxonomy for graph visualization *(BELIV '06).* ACM, 1–5.
[16] Vinayak Mathur and Arpit Singh. 2018. The Rapidly Changing Landscape of Conversational Agents. (/03/22 2018).
[17] Kayla Matthews. 2018. We Need to Talk About Biased AI Algorithms.
[18] Michael Mctear. 2002. Spoken dialogue technology: enabling the conversational user interface. *ACM Computing Surveys (CSUR)* 34, 1 (2002), 90–169.
[19] Fernando A. Mikic, Juan C. Burguillo, Martin Llamas, Daniel A. Rodriguez, and Eduardo Rodriguez. 2009. CHARLIE: An AIML-based chatterbot which works as an interface among INES and humans. , 6 pages.
[20] Adam S. Miner, Arnold Milstein, Stephen Schueller, Roshini Hegde, Christina Mangurian, and Eleni Linos. 2016. Smartphone-based conversational agents and responses to questions about mental health, interpersonal violence, and physical health. *JAMA internal medicine* 176, 5 (2016), 619–625.
[21] Maximilian Nickel, Kevin Murphy, Volker Tresp, and Evgeniy Gabrilovich. 2016. A Review of Relational Machine Learning for Knowledge Graphs. *Proc. IEEE* 104, 1 (2016), 11–33.
[22] Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z. Berkay Celik, and Ananthram Swami. 2017. Practical Black-Box Attacks Against Machine Learning. ACM, New York, NY, USA, 506âĂŞ519.
[23] Eric Prud'hommeaux and Andy Seaborne. 2008. SPARQL Query Language for RDF.
[24] Marco Tulio Correia Ribeiro. 2016. Lime.
[25] Marco Tulio Correia Ribeiro. 2016. Lime: Explaining the predictions of any machine learning classifier.
[26] Scott Robertson, Rob Solomon, Mark Riedl, Theresa Wicklin Gillespie, Toni Chociemski, Viraj Master, and Arun Mohan. 2015. *The visual design and implementation of an embodied conversational agent in a shared decision-making context (eCoach).* Springer, 427–437.
[27] Daniil Sorokin and Iryna Gurevych. 2018. Modeling Semantics with Gated Graph Neural Networks for Knowledge Base Question Answering.
[28] Seema Sundara, Medha Atre, Vladimir Kolovski, Souripriya Das, Zhe Wu, Eugene Inseok Chong, and Jagannathan Srinivasan. 2010. Visualizing large-scale RDF data using Subsets, Summaries, and Sampling in Oracle. , 1048-1059 pages.
[29] Wen tau Yih, Matthew Richardson, Christopher Meek, Ming-Wei Chang, Jina Suh, and Microsoft Research Redmond. 2016. The Value of Semantic Parse Labeling for Knowledge Base Question Answering.
[30] J. J. Thomas and K. A. Cook. 2006. A visual analytics agenda. *Computer Graphics and Applications, IEEE* 26, 1 (2006), 10–13.
[31] (TM) TopQuadrant. [n. d.]. TopBraid Application.
[32] (TM) TopQuadrant. [n. d.]. TopQuadrant SPIN Inferencing.
[33] A. M. Turing. [n. d.]. Computing Machinery and Intelligence Author(s): A. M. Turing Source: Mind, New Series, Vol. 59, No. 236 (Oct., 1950), pp. 433-460 Published by: Oxford University Press on behalf of the Mind Association Stable URL: http://www.jstor.org/stable/2251299.
[34] Jane Wakefield. 2016. Would you want to talk to a machine?
[35] Ruijie Wang, Yuchen Yan, Jialu Wang, Yuting Jia, Ye Zhang, Weinan Zhang, and Xinbing Wang. 2018. AceKG: A Large-scale Knowledge Graph for Academic Data Mining.
[36] Chen Wei, Zhichen Yu, and Simon Fong. 2018. How to Build a Chatbot: Chatbot Framework and Its Capabilities. ACM, New York, NY, USA, 369âĂŞ373.
[37] Joseph Weizenbaum. 1983. ELIZA - a computer program for the study of natural language communication between man and machine. *Commun. ACM* 26, 1 (1983), 23–28.
[38] Rudolf Wille. 2006/10/30. Formal Concept Analysis as Applied Lattice Theory. Springer, Berlin, Heidelberg, 42–67.
[39] Christophe Willemsen. 2018. 3 reasons why Knowledge Graphs are foundational to Chatbots.
[40] Christophe Willemsen and GraphAware. 2018. Knowledge Graphs and Chatbots with Neo4j.
[41] B. L. William Wong, Patrick Seidler, Neesha Kodagoda, and Chris Rooney. 2018. Supporting variability in criminal intelligence analysis: From expert intuition to critical and rigorous analysis. *Societal Implications of Community-Oriented Policing and Technology* (2018), 1–11.
[42] B. L. W. Wong and Margaret Varga. 2012. Black Holes, Keyholes And Brown Worms: Challenges In Sense Making. , 287-291 pages.
[43] BL William Wong and Ann Blandford. 2004. Describing Situation Awareness at an Emergency Medical Dispatch Centre. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 48. SAGE Publications Sage CA: Los Angeles, CA, 285–289.