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# DESIGNING A SYSTEM TO MIMIC EXPERT COGNITION: AN INITIAL PROTOTYPE

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*In this paper, we present a proof-of-concept system to highlight the potential benefits of mimicking higher-order cognitive processes involved in 'insight seeking' to create the necessary context for expert sensemaking. We draw upon data from a realistic investigation exercise undertaken by 14 experienced intelligence analysts and use this to develop our prototype to mimic behaviours demonstrated by expert analysts. Our prototype system evaluates different strategies and provides recommendations for an analyst to explore, through a prototype user interface. The recommended strategies, and associated information retrieved, aligns with the actual investigations. We propose that our system presents a novel and promising approach to design AI support systems for tasks that typically require human expert cognitive processes.*

## INTRODUCTION

Intelligence analysis involves complex reasoning and analysts make use of their expertise to inform cognitive processes that are not easily emulated by computer systems. Cognitive mimetics is where a system is designed to mimic human information processing (Kujala and Saariluoma, 2018) and this could help an analyst, if by understanding and mimicking higher order cognition the system could more effectively augment expert reasoning. We propose that intelligent systems can learn from human expertise, and in this paper, we present a proof-of-concept prototype system that captures and mimics the higher-order cognitive processes involved in insight seeking. The system aims to create the context from which insights can emerge.

This paper is organised as follows:

1. We introduce the nature of insight in criminal investigations and the limitations of typical Artificial Intelligence (AI) systems.
2. We provide some background to a conversational agent system, called Pan (Hepenstal et al. 2021a) and designed for intelligence analysis.
3. We provide a short overview of a user study to capture insight seeking behaviours, strategies and behaviour sequence rules from interactions with a question-answer system (Hepenstal et al. 2021b).
4. We demonstrate an example implementation for how cognitive behaviours can be used to recommend strategies for lines of inquiry.
5. We conclude that our proof-of-concept system is an example of cognitive mimetics.

## THE NATURE OF INSIGHT IN INVESTIGATIONS

Criminal investigators are required to find and make sense of fragmentary, out of sequence, missing, unknown, and ambiguous data. To do this, investigators must reason from the available data to a hypothesis that explains the data (Walton, 2005). The process is not straightforward and involves expert sensemaking, with limited resources and time available. There are numerous models that describe sensemaking (Ancona, 2011; Klein et al., 2007; Czarniawska, 1997). In this paper, we are particularly interested in the cognitive processes that allow investigators to comprehend a situation and support their decision making, described by Gerber et al. (2016) as insight, and highlighted in a model of decision making. Gerber et al. (2016) notes that insight is the outcome of deliberate analysis. Analysts utilise their expertise to intelligently explore both new and known information, informed by their beliefs about the situation. These beliefs are anchors, including supposed facts or entities that are perceived as being important. This is how analysts create the environment from which insights are derived. Klein describes the importance of anchors with a triple path 'Anchor model of insight' (Klein and Jarosz, 2011). The paths comprise: (1) Contradiction: an inconsistency is found and a weak anchor is then used to rebuild a story. (2) Connection: an implication is spotted and a new anchor is added to the set. (3) Creative desperation: an anchor is discarded, to escape an impasse.

## EXPERT REASONING AND AI SYSTEMS

Significant technological advances have been made over recent years and AI systems can perform some complex tasks that traditionally required human intelligence. Machine learning (ML) is a key feature that allows systems to learn directly from data, to identify patterns and make decisions, such as predictions, without human oversight. There are, however, limitations to the current ML and data focused approach, as outlined by Chui et al. (2018). Two critical limitations relate to the data: both the labelling of data and access to massive training data sets. As a result, current ML approaches are narrow, tailored to solve specific problems and constrained by the data used to train the algorithm. In situations where data is not available and explanatory reasoning is required, we need to be careful when considering how to utilise the capabilities of AI technologies. For intelligence analysis, where data is at best incomplete, at worst inaccurate or deliberately deceptive, a system needs to sufficiently appreciate the significance of seemingly minor, coincidental, or unusual aspects within the context of the overall situation. The reasoning required to do this from little information to deliver a level of understanding, whilst appreciating gaps, uncertainties, and caveats, is innately human. A different perspective on AI system design is that, in order to support human expertise, "it is necessary to model and mimic many levels of physical and intellectual work", towards cognitive mimetics i.e. "the mimicry of higher cognitive processes for designing intelligent technology" (Kujala and Saariluoma, 2018). Returning to the recommendation problem, if we understand how analysts seek information in an investigation and any strategies or behaviour patterns they exhibit to reach a claim, this could help a system to recommend and reward appropriate lines of inquiry that provide the right information to aid insights.

## PAN CONVERSATIONAL AGENT (CA) SYSTEM

The prototype system described in this paper draws upon previous work by Hepenstal et al. (2021a) to develop a conversational question-answer system, called Pan. The Pan system can respond to natural language questions from a user by matching their utterances to an 'intent', through text classification, where each intent triggers a series of functional processes to query, manipulate, and respond with relevant data. As users interact with Pan, the questions asked can be captured in addition to the related intent, which can be broken down to describe the specific functional processes involved. In previous work, Hepenstal et al. (2020) demonstrated how question networks can be formed from conversational interactions, which capture semantically domain relevant possibilities for lines of inquiry.

## LIMITATIONS: THE CHALLENGE WITH RECOMMENDING LINES OF INQUIRY

Investigations are intellectually challenging and, when considering how to recommend a line of inquiry, it is not simply a case of retrieving information until a solution is found. There is often a very large amount of information available to an analyst; much more than it is possible to explore or comprehend. Furthermore, investigations are not an exact science with a single 'right' answer. They involve reasoning over incomplete information and the use of abductive inference. It is the combination of useful information, awareness of information gaps, and expert reasoning to derive insights, that achieves a solution. Analyst expertise helps deal with the ambiguity that exists about which lines of inquiry to pursue and what information should be presented to support reasoning. Such an intellectually challenging process is difficult to predict and optimise. We need to consider what makes a good line of inquiry, or what metrics can be calculated to appropriately reward and compare different lines of inquiry. To understand how best to recommend lines of inquiry, we need to consider the context that underlies how an analyst gathers and interprets the available information to arrive at a claim. Rather than designing systems to search for the 'right' answer autonomously, in this paper we look to optimise the opportunity for insights. If the context for insight can be learned from the way that an analyst constructs the frame from which insights emerge, we can design systems to create this context, mimicking higher order cognitive processes.

## USER STUDY: SUMMARY

We have drawn upon the data and findings from a previous study, reported by Hepenstal et al. (2021b), to develop our proof-of-concept prototype. An overview of the study, analysis and results are provided here.

**Purpose, participants, and equipment:** To understand the context for insight, 14 investigation exercises were performed with operational intelligence analysts. Analysts could pose questions to Pan and could then display and interact with the data retrieved via a network graph visualisation. Pan collected data from the questions asked by analysts, including the input entities, query classes, and their intent.

**Investigation exercise:** Each analyst was asked to conduct an investigation by asking questions and retrieving information from Pan. Various hypotheses could be reasoned from the scenario data and the exercises ended when the analysts articulated a plausible hypothesis, or claim, about the situation, based upon the data they had retrieved.

## CAPTURING INSIGHT SEEKING BEHAVIOURS, STRATEGIES AND RULES

Hepenstal et al. 2021b, described how it was possible to classify insight seeking behaviours from the questions posed by analysts, based upon the anchors used in each question and the context of the investigation. These behaviours were aligned to the triple path model of insight presented by Klein and Jarosz (2011). Hepenstal et al. (2021b), also demonstrated how insight seeking strategies and rules could be captured from the analyst investigations using the RuleGen algorithm (Zaki, 2000). The rules are sequences of behaviours that occurred prior to claims in the investigations, and thus help capture the necessary precursor steps that provide the context for insight. An example of an insight seeking strategy and respective behaviour encodings, is shown in Table 1.

Table 1: Example of a significant strategy used by 4 analysts (Hepenstal et al. 2021b).

| *Analyst* | *Utterance* | *Part* | *Response* | *Insight seeking* |
|---|---|---|---|---|
| *A4* | '*What is Susan Leech linked to?*' [10:35] | 1 | Data is found, results include a domestic assault activity. | Seek implications from level 0 |
| *A4* | '*So, I'd want to know who the offender was (in the domestic assault activity).*' [11:25] | 2 | Data is found, results include a person called Paul Richards. | Seek implications from level +1 |
| *A4* | '*How is Paul Richards linked to Dan Govey (a known anchor)?*' [12:10] | 3 | | Seek contradictions from level +2. |

## PROTOTYPE SYSTEM DESIGN AND IMPLEMENTATION

In this paper, we describe how we have designed a conversational system to dynamically capture and apply insight seeking behaviours and strategies to intelligently explore and recommend lines of inquiry. Our implementation incorporates the modelling of conversational user interactions across various levels, including the question intent, domain context, and cognitive behaviour. The system can select and explore the best insight seeking strategies, based upon an understanding of possible future strategies and the sequence rules they meet, given the behaviours already displayed. The prototype system can then use a selected strategy to define how to manipulate anchors when posing domain relevant questions. We have compared our approach with the investigations performed by analysts, retrospectively.

## STRATEGY RECOMMENDATION METHOD

To identify which insight seeking strategy to follow at any given point in an investigation, we needed a method that could assess the relative likely value or reward that could be gained by following each strategy, with an appreciation of the overall state of the investigation. Understanding reward accurately is a critical problem with potentially considerable benefits, for example, for reinforcement learning algorithms (Silver et al. 2021). There are numerous examples, however, where the environment or reward is poorly defined and this has led to an AI system ending up with the wrong goals (Marcus and Davis, 2019), known as the 'alignment problem' (Christian, 2021). A deep understanding of the context of a task and the needs of a user is required to appropriately configure reward, particularly in the case of explanatory reasoning activities where rewards are intangible.

For a given line of inquiry we calculated which sequence rules had been met, the length of the rules met, which rules were outstanding, and possible follow-on strategy chains to meet these rules. The rules were the sequences of behaviours that occurred prior to a claim, indicating the necessary precursor steps to construct the context for insights. Thus, the sequence rules helped provide tangible rewards for lines of inquiry, where the system could aim to match a higher number of rules. Strategies could only be used if they started with the final behaviour of the previous strategy, so this reduced the possibilities. By calculating insight seeking rules we could determine the relative value of each strategy chain and rank them accordingly. To rank strategies and visualise chains in a simple and transparent way, we constructed a decision tree for each strategy selection. The tree identified the possible follow-on strategies, for up to three steps from the initial strategy. An example of strategy chains and the decision tree is shown in Figure 1.

Longer rules were deemed to be most desirable, given that these captured more informative precursor steps and associated relationships between behaviours whilst also encapsulating shorter rules. We therefore decided to reward strategies based upon rule length rather than count. We created rule scores for the leaf nodes of the tree, accounting for the sequence of strategies used to reach them and the average length of rules met by the sequence. Each rule had an associated confidence based upon usage by the analysts in the user study and calculated by the RuleGen algorithm. The rule lengths were weighted accordingly, prior to calculating the average. This approach allowed us to ensure that strategies were selected that would maximise the length of rules, whilst appreciating the relative confidence of the rule. We have used a maximin approach to rank the possible strategies to ensure that strategies were not recommended that required specific follow-on strategies in order to be beneficial.

## STRATEGY SELECTION RESULTS

The decision tree approach was effective at making strategy selections that were likely to increase the number of rules met in a line of inquiry. We tested whether our approach achieved strategy selections that delivered a high number of rules by using it to select 5 strategies in sequence, comprising 13 interactions (this was the average number of interactions performed by analysts in their investigations). The first strategy selected started with a 'Seek implications' behaviour. This aligned with the first question posed by the analysts in their investigations. The optimal suggested sequence of strategies using the decision tree method met 75 rules. This is far higher than if we were to select strategies at random: the average number of rules met from 1000 sequences of 13 randomly selected behaviours was a little over 10 rules. Compared retrospectively to the investigations performed by analysts, our method also met more rules than the median and mean average number of rules met (median = 28, mean = 32.5). One analyst met a greater number of rules in their investigation (124), however they also had more interactions with the system (21). Thus, the decision tree approach was deemed effective at selecting strategies comprising behaviour sequences that occur prior to claims.

On inspection, the recommended strategies appear sensible. For example, if we imagine an investigation where five 'seek implications' behaviours have been performed in sequence and the next strategy begins with another 'seek implications' behaviour, it may be helpful for the system to recommend a strategy that considered a different angle or sought inconsistencies to help check any results. Given this situation, our method identifies the top 3 highest ranked strategies and all involve escaping impasse or seeking inconsistencies (as shown in Figure 1). The lowest ranked 3 strategies involve seeking implications only. The strategy rankings therefore sensibly prioritise more diverse insight seeking behaviours given the stage of the investigation.

It is not always possible to perform a strategy depending upon the response to each behaviour and this is influenced by the data available and the constraints of the domain. It was therefore important that if a 'best' strategy could not be taken, a user could instead select the next best, or the next best after that. Our approach allowed for the tree to be redrawn dynamically, as strategies were selected and followed, and the best routes to meet remaining rules were recalculated. The decision tree approach also allowed the strategy ranking to be easily explored by a user, where they could delve into a visualisation of the tree itself, if necessary, to inspect and verify the goals and constraints of the method and compare the relative values of different strategy combinations. The nature of investigation support systems that provide recommendations for lines of inquiry raises questions about the possible manipulation of analysts, or reduction of analyst expertise due to their reliance on a system. System transparency is, therefore, an important consideration.

There are many alternative approaches that could be applied for strategy selection and future work should explore these. The approach we have applied could certainly be improved to deliver a more optimal sequence, however, we feel this method is sufficient to provide a proof-of-concept that demonstrates how recommendations can be guided intelligently with an understanding of the cognitive context. An analyst can select a strategy then perform it step by step, remaining in control of the interpretation of results and selection of specific inputs and queries.

## PROTOTYPE SYSTEM RECOMMENDATIONS

We retrospectively compared the lines of inquiry undertaken by analysts during their investigations with recommendations from our system. We found that our prototype system mimics analyst behaviours to create frames similar to those observed in the investigations, given the state of the investigation. For example, all the analysts opened their investigations with the same question, `"What mobiles have been involved in call events with IDMOB1?"` This question demonstrated the insight seeking behaviour of seeking connections or implications for the entity of interest (IDMOB1) and returned new results including IDMOB3 and IDMOB4. Following this initial question, the second question asked by analysts 1, 4, and 5 was to find what information was known about IDMOB3, specifically who could be the owner or user of IDMOB3. They hoped any information returned would help them to draw connections that could inform insights, and their insight seeking behaviour was, therefore, seeking implications. We used our system to recommend and explore lines of inquiry from this point, mirroring analysts 1, 4, and 5. Figure 2 shows the strategy explorer interface. The system applied the decision tree methodology described earlier and proposed that the optimal strategy was to:

(1) Seek further implications, using the results to the question '*Who is linked to IDMOB3?*'
(2) If data returned, seek implications from new data.
(3) If data returned, seek inconsistencies with new data.

This recommended strategy matches the actual investigation exercises. For example, Analyst 1 (A1) found that Susan Leech was the owner of IDMOB3 and asked `"Who are Susan Leech's associates?" [Analyst 1; timestamp 12:10].` They were seeking further implications from the most recent results returned by their previous question, at the highest level of their line of inquiry. Their query found a person called Paul Richards, who had been involved in a domestic assault incident where Susan Leech was the victim. The analyst was aware that Dan Govey was an important anchor for their line of inquiry and wanted to understand the significance of the new entity, Paul Richards. They looked for any association between the two and said, `"Ok, so the next obvious question is, is Paul Richards connected to Dan (Govey)?" [A1; 12:45].` The analyst found that Paul Richards was connected to Dan Govey via DGX Bodywork and they completed the investigation exercise with an explanatory hypothesis. Specifically, they identified that `"Susan and Paul, (are) probably other halves of each other"` and, `"Paul does have a shortest path connection to (DXG) Bodyworks".` They concluded, `"that would be good enough I think for me to put a tentative connection between Paul and our unknown number". [A1; 21:13-21:45]` Their insight seeking strategy had a direct influence on their claim, where the analyst cross-checked the relationship between the two anchors of interest (Dan Govey and DGX Bodywork) and when they found a connection this was important for their explanatory hypothesis. Had no connection been found, the analyst may have interpreted the data differently. For example, Analyst 3 did not find this connection, and thus was unsure about their hypothesis. `"If we hypothesise that this is Paul Richard's phone, then there is no current connection between Paul Richards and Dan Govey. We've either established a (new) link, or that kind of goes against it in that there is not already a confirmed link there. " [A3; 29:10].`

There were numerous other examples of insight seeking strategies suggested by the system that retrieved data that directly informed analyst hypotheses in the investigations.

## DISCUSSION AND CONCLUSION

The prototype system presented in this paper provides a working demonstration of the exciting potential of cognitive mimetics. By modelling the cognitive behaviours of investigators, we demonstrate how a system can then support the exploration of lines of inquiry and mimic expert cognitive strategies. Our application of an abstract, cognition based, approach, potentially mitigates biases in the data that would influence alternative methods to predict and optimise lines of inquiry. The system described in this paper is an early proof-of-concept and has not been evaluated with users. Further work is needed to understand the benefits of this system, including the usefulness, usability, desirability, and impact on decision making, of both the system and the concept of cognitive mimetics. There are numerous areas for further work, including increasing the size of the insight seeking behaviour dataset, applying more advanced methods to evaluate and recommend lines of inquiry, and exploring how a user should interact with recommendations from the system.

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Figure 1: The example strategy tree provides strategy rankings in descending order. Each node represents a strategy that can be followed given the parent strategy. The recommended strategy in this case is to escape impasse and begin a fresh line of inquiry.

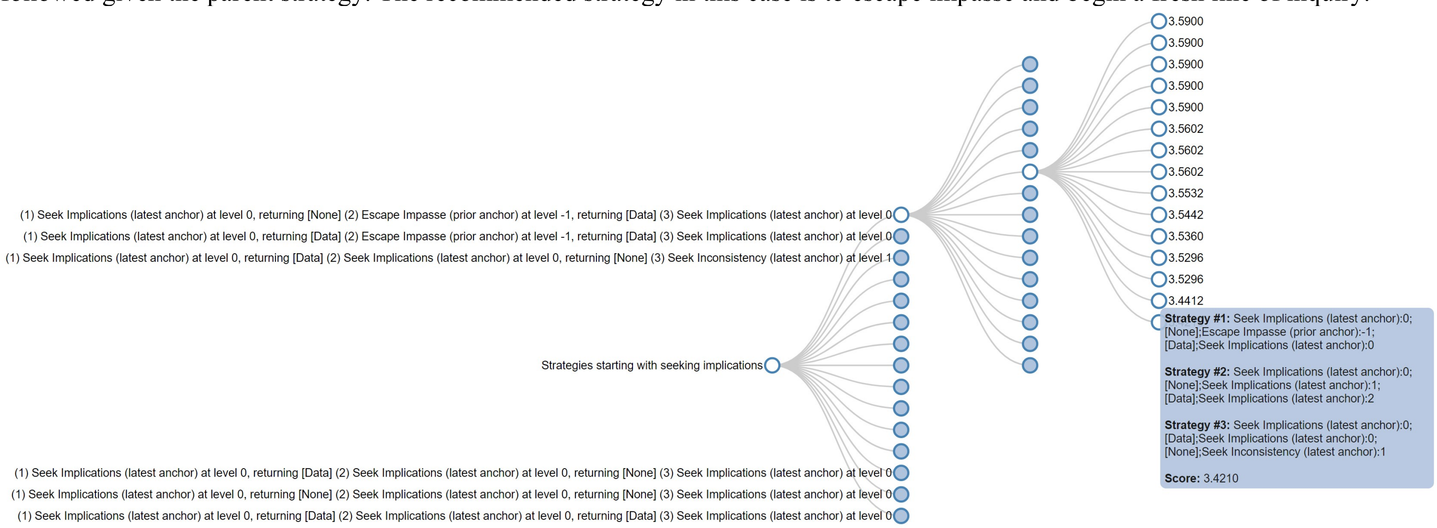


Figure 2: User Interface for strategy exploration. An analyst can open the strategy exploration interface from a question they have asked. The possible strategies are calculated and ranked. A user can explore, inspect, configure, and verify the strategy tree (Figure 1) by clicking on the icon next to 'Strategy Rankings'. When a strategy has been selected, the analyst can choose specific queries and search methods. Results are fed into the anchor set and can be selected as inputs if they are at the right anchor level.