

# Capturing Sensemaking Pattern during Data Analysis: A Conceptual Framework

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## Abstract

Sensemaking is often associated with processing large or complex amounts of data obtained from diverse and distributed sources. Sensemaking is an important process for any business, since it deals with understanding data and facts that relate to unknown or ambiguous situations. To-date, the research base on sensemaking has not moved far from the conceptual realm however. Our vision here is to operationalise sensemaking in order to improve the human decision-making process (ultimately in the context of large data volumes in a business context). This study contributes to the knowledge base by proposing a novel conceptual framework that utilises Data Mining (DM) and Machine Learning (ML) to assist in transforming user interactions with the analytical software that models sensemaking patterns. These patterns reflect people's experience during the analysis and exploration of the data related to the emergent ambiguous situation.

**Keywords:** Sensemaking, Data Mining, Machine Learning.

## 1. Introduction

Decision making is one of the basic cognitive processes of humans, traditionally seen as choosing a preferred option or a course of actions from among a set of alternatives based on previously defined criteria. In reality, however, problems within organizational and social realms are often difficult to explicitly model and (completely) formalize – often due to the constraints within organizations, people, data, technology, functionality, time, budget and resources [27]. In addition, decision criteria and alternatives are burgeoning due to the continuing increase in the Variety, Volume, Veracity, Velocity and Value (5Vs) of (big) data [4]. Thus, a challenge in relation to understanding and making sense of data are coming to the fore [2]: ‘Big data’ arguably, therefore, requires ‘big insight’.

As a response to this challenge, there is an increasing focus on the development and application of technologies and concepts that have emerged such as data mining and machine learning. Less of a focus has been placed on how people actually make sense of data in their day-to-day activities however. Sensemaking is concerned with studying how people comprehend and analyse events and data that are characterised with ambiguity and equivocality [32]. At its simplest, sensemaking can be described as the interrelated recurring processes of noticing, interpreting and action [14]. Noticing, is a process in which individual actors single out some problematic stimuli as cues for further conscious processing out of their streams of experience in the situations that they face. Interpretation is a combining process in which the cue and data are connected to a frame of reference, through which meaning of the cue is constructed and hypotheses are generated. Lastly, action represents the current ‘work’ that is motivated by a future goal and at the same time makes it real. Action often triggers subsequent sensemaking (noticing and interpretation) [14].

The discussion on sensemaking has not moved far from the conceptual realm to-date. Our vision here is to operationalise sensemaking process by intelligently capturing the analysis ‘experience’ during data analysis life cycle. The objective is to harness the power of data mining and machine learning techniques to improve human decision-making process (ultimately in the context of large data volumes in a business context). In starting on this journey, the remainder of this paper is structured as follows. Section 1.1 highlights the importance of sensemaking research. Section 2 reviews the related work in different research communities and explains the similarities and differences among them. Section 3 introduces and describes our conceptual framework. Section 4 defines the application context where the proposed framework will be tested and validated, explaining the methodology that will be adopted. Finally, Section 5 concludes the work and explains the future work required to advance this research.

### **1.1 Importance of Sensemaking**

Sensemaking can be seen as the process that generates the heuristics, cues, options and hypotheses, which together form a *frame of reference* that is (implicitly) consulted when a new (ambiguous) situation triggers the sensemaking process [17]. Consequently, sensemaking support systems are qualitatively different from (traditional) decision support systems. The latter type helps decision makers with known situations by facilitating the comparison of alternative solutions or decisions – effectively optimising the decision space. Sensemaking support systems, on other hand, help actors with equivocal and ambiguous problems that require constructing (and/or reconstructing) frames of reference, in order first to understand the factors that trigger the sensemaking process [24]. Zack [35] argues that traditional Decision Support Systems are valuable in the context of uncertainty and complexity, but that they are lacking in the context of ambiguity and equivocality. Given that the latter are arguably prevalent in the social and organisational realm, there is a need to help decision-makers to better deal with ambiguous and equivocal (emergent) challenges – especially in rapidly changing conditions within organisations [10].

## **2. Sensemaking in the Literature**

Sensemaking provides the ability to deal with rapidly emerging threats as well as asymmetric, unfamiliar, and dynamic situations: Though Weick’s work [32], [34] is pivotal in the organisational realm, sensemaking has reared its head in other domains. We now therefore discuss sensemaking from business, enacted cognition and computational perspectives.

### **2.1. Sensemaking in the (Strategic) Organisational Literature**

Weick’s work [32], [34] provides a fundamental grounding of sensemaking within organisations. He defines sensemaking as the process where people generate their own understanding and interpretations of certain situations. Thus, sensemaking can be seen as a continuous retrospection, where beliefs, implicit assumptions, stories from the past, unspoken premises for decision, actions, and ideas about what will happen as a result of what can be done, are gathered to form an acceptable understanding or sense that is described with clear rules and words. Nevertheless, the generated sense is affected by selective perception, since only some aspects of the world are considered, while others are forgotten or neglected. The distinguishing features of sensemaking are listed in Table 1.

Other works in the area focus on characteristics, features and functionalities such as the recurring process of creating and modifying views and visions about ambiguous issues and situations [10], the importance of the past experiences in shaping the primary assessments [10], [18], providing explanations and attributes for the emergent events and predicting the following ones [10], [12], [18], the ability to build relations between views, expectations and actions [18], the ability to create rational accounts of the world that enable actions [12], [28],

and finally, the ability to extract , interpret and explain cues from people’s environment [21], [29], [32].

**Table 1.** Sensemaking features

Feature	Description and Justification
The identity of the sense maker	Sensemaking is grounded in the identities of the sense makers who continually redefine their perception of themselves and the situation they face.
Retrospective	Because, a never-ending reconstruction of experience occurs.
Enactive	Enactive of the working environment, because people create or enact their environment by interacting with it and among each other based on the knowledge gained through physical actions as well as individuals’ own skills and perceptions.
Social and Systematic	Social and Systematic, since it occurs between people inside and outside the organization.
On-going	On-going, because sensemaking is a continuous process.
Plausibility	Driven by plausibility rather than accuracy, since the absolute accuracy is impossible in an equivocal and changing world where stakeholders go through guesswork, subjectivity, and arbitrariness
Noticing and labelling	Sensemaking happens by noticing and labelling cues emerge from data and actions

Recent studies have concentrated on the social nature of organisational sensemaking. These studies have focused on language, rather than cognition as the enabler of sensemaking [3], [19, 20, 21], [33]. Similarly, emotion as a dimension is also receiving some attention [22] – negative emotion, in particular, is considered of a particular importance in crisis situations as well as organisational change [7], [21]. Negative emotion can take the form of fear, desperation, anxiety and panic, which can significantly affect individual cognitive information processing ability as well as the capability to notice and extract cues [21], [29]. Conversely, it has also been demonstrated that planned organisational change can generate positive emotions that help the involved stakeholders to understand the change initiative [21]. The point, however, is that the significance of emotion stems from its role as the necessary triggering factor that initiates the sensemaking process [7].

## 2.2. Enacted Sensemaking Perspective

The enactive cognition literature examines how individuals use interaction to perceive and then shape their world to create meaning and value [32] – concentrating on the dynamics of that in good part. Enactive cognition is based on key principles such as the *autonomous* nature of an individual, the emergence of an individual’s world through their interaction with the world, the embodiment of the learning process and, finally, the importance of experience in comprehending situation [30, 31].

Autonomy asserts that agents continuously regenerate their own understanding of the environment they are interacting with and through [5]. Adaptivity provides the tolerance to face and deal with the emergent and varying challenges during the communication in the environment [6]. Consequently, sensemaking is defined as the interaction and the engagement of a system (typically an individual) with its environment via a relational process. Addressing the social perspective, interaction is seen as a sustainable coordination between individuals, where additional meaning and value is created [5].

## 2.3. Computational Sensemaking Perspective

The computational sensemaking literature examines the phenomena in a way that seeks to operationalise it. One stream centres on situational awareness, exploring how the cognitive capability of human mind uses non-stop creativity, curiosity, perception, comprehension, projection and mental modelling to form the sense out of people’s experiences – typically in the form of heuristics, cues and hypotheses [1], [15], [17]. Much of the background here comes from studies of Naturalistic Decision Making (NDM), studying cognition in real-world environments that are characterised by ill-structured problems, uncertain and dynamic

environments, ill-defined and competing goals, time stress, high stakes, multiple participants and important organizational goals [25].

The naturalistic approach seeks to empirically trace the ‘paths’ that humans take in making sense of the world. One school of thought structures this process in two main iterative loops derived from Cognitive Task Analysis (CTA) studies, see Figure (1a): 1) A *foraging loop*, where sense makers seek information about the ambiguous problem and generate examples and hypotheses that can provide answers; and 2) a *sensemaking loop*, in which sense makers iteratively develop a mental model that best fits the examples and hypotheses generated in foraging [17], [26].

A second (but related) school examines how people start the sensemaking process by constructing a basic and minimal frame which allows them to have some view on the problem at hand. This frame can be further developed by the addition of details and questioning the explanations the initial frame delivers. Ultimately, this can lead to preserving or elaborating the frame, or to start a reframing cycle, in which new, better and enhanced frame is created [16]. This model, see Figure (1b), was examined in a crisis situation and demonstrated how the loop of framing, questioning and reframing has proved its potentials to model human’s intelligence and sensemaking process [23].

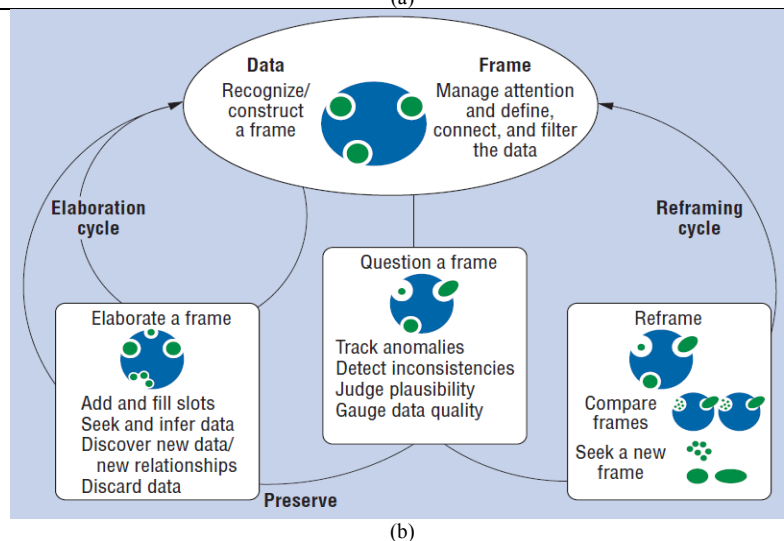
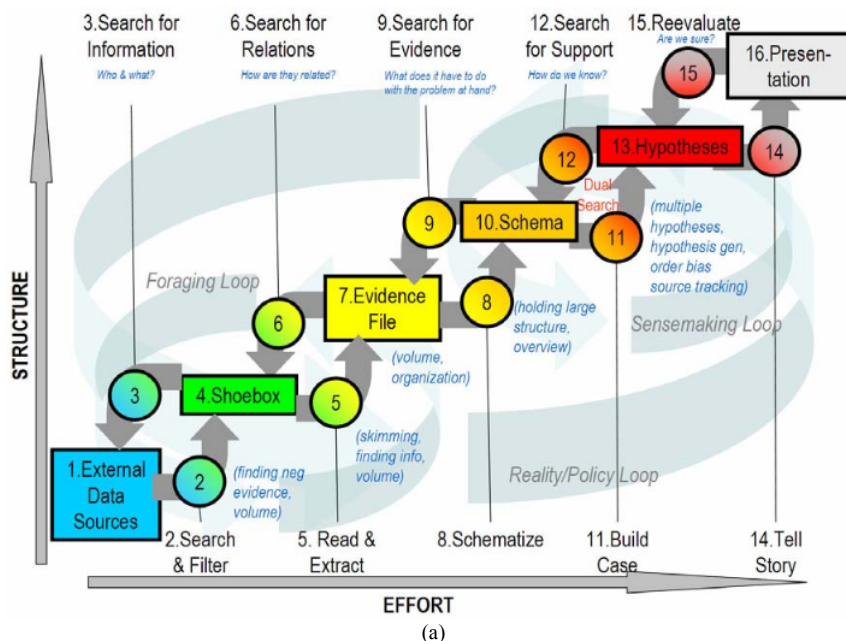
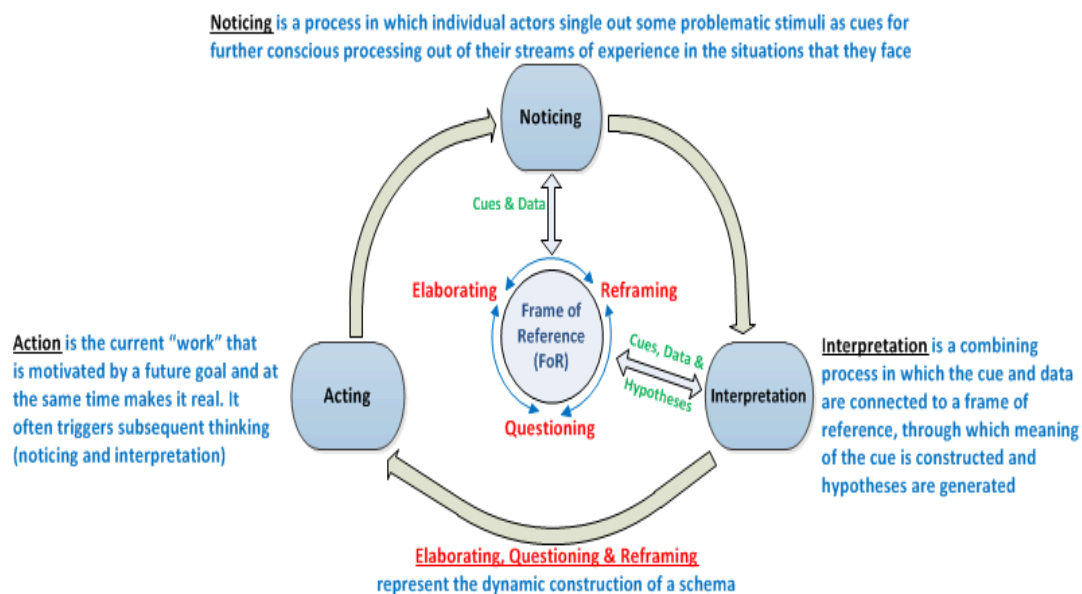


Fig 1. Sensemaking models a) Notional sensemaking model (adapted from [26])  
 b) Data/Frame model (adapted from ([16])

### 3. Toward a Computational Sensemaking Framework

Despite the fact that sensemaking accounts are generated in different domains at different times, a number of similarities arise. First, all accounts study the retrospective nature of how individuals shape their world via recurring interaction and the creation of meaning and value. Second, both organisational and enactive literature, examine how new knowledge is created via a continuous (social) interaction with the environment they interact with and/or exist within. Third, the enactive and computational approaches in particular, seek to put some ‘flesh on the bones’ in identifying constructs generated from the sensemaking process such as frames of reference, cues, hypotheses etc. Thus, the computational literature proposes sensemaking models by identifying concepts such as foraging, framing, elaboration and reframing. As the state-of-the-art stands, however, there is little in the way of research that examines how to make these constructs operational using current/emerging computational techniques.

Our synthesis of the current literature is shown diagrammatically in Figure 2. The noticing, interpreting and acting loop are considered as the core processes that inform/reform a Frame of Reference (FoR); this is a schema that contains and connects cues and, in addition, contains the hypothesis/hypotheses about the problem under investigation. In this model, sensemaking process starts with *noticing*, which is the process of cue extraction, then, *interpretation*, which is the process of structuring cues, developing (competing) hypotheses and selecting the most likely as a precursor to make *actions* based on the interpretations. An inner loop represents the ongoing dynamics of that process via the questioning of a frame (as a reflection on action), elaboration of a frame and, ultimately, reframing.



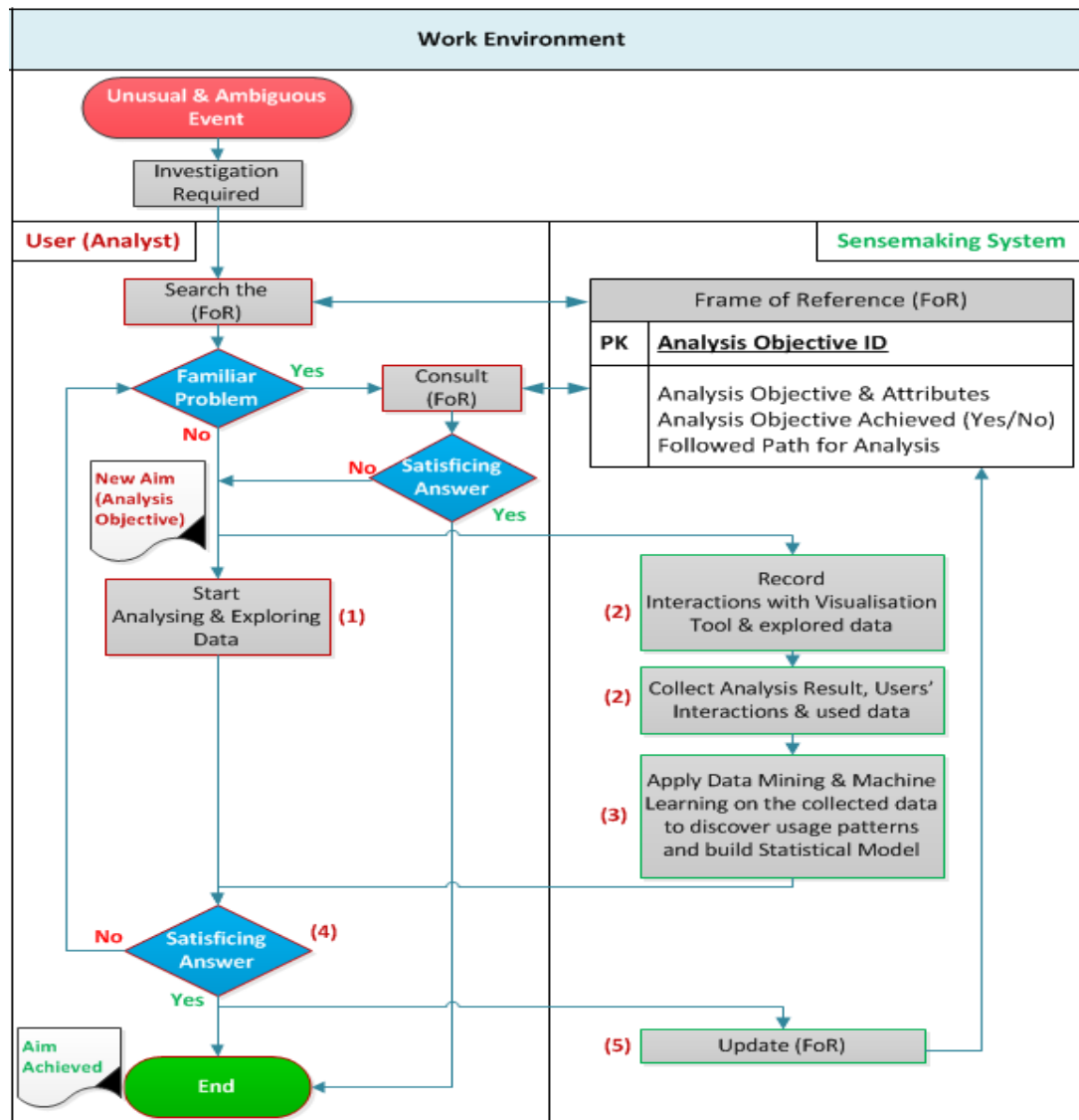
**Fig 2.** Conceptual sensemaking model

We conceptualise the FoR as a schema that holds the question(s) driving an analytical event, the cues (data) that are seen as important in relation to the analysis task, the relations between those data (which can be taken as an initial hypothesis), and the findings seen as the satisficing answers. Table 2 lists the elements that form the FoR as well as their descriptions. Our aim is to operationalize this framework in the context of (business) analysts going about their daily business, following the process shown at Figure 3. This process model embodies the work environment, where an analyst uses (interacts with) software to analyse and visualise data. In addition, the work environment symbolises the sensemaking system that captures and mines user interactions with the analytical software. The interactions will be captured using specialised software that has the capability to record mouse clicks and keyboard strokes in two formats, as a written text and as a screenshot, which will be further processed in order to transform them into a time series data that reflect user’s interactions.

**Table 2.** Frame of Reference (FoR) Elements

FoR Element	Description
Analysis question(s)	The event or task that triggers the sensemaking process
Findings	The answers or results that are seen as satisfying for the analysis question
Analysis task successful	Yes \ No
User-Software data exchange	The data exchanged between the user and the software
Cues	The data that are important for the current analysis task
hypothesis/hypotheses developed during analysis	The initial as well as the modified hypothesis throughout the sensemaking life cycle

We envisage that, at the beginning of a task, the analyst could consult the (computational) Frame-of-Reference for similar use cases in order to check the hypotheses and findings previously generated for similar problems. In the absence of a prior use case, the sensemaking system will log the user interaction with the data analysis and visualisation tool. Then, interaction pattern mining techniques [9] will be applied to the log to discover usage scenarios that help to uncover the analytical cues of importance and the relationships between them, which form a hypothesis for how to solve the analytical task.



**Fig 3.** Process model to operationalise sensemaking process

We expect that the analytical ‘paths’ that result will differ across analysts working on the same task, reflecting analyst’s experience and prior technical and domain knowledge.

Consequently we expect that there may be multiple paths taken in achieving the same analytical objective. This means that the outcomes of consulting the computational Frame-of-Reference will likely differ across analysts interacting with the software. Where differences are minimal, patterns may be observed. Where differences are more marked, we believe it will be necessary for computational mechanisms to evaluate competing hypotheses (this aspect can be thought of as part of the inner questioning, reframing, elaborating cycle in the conceptual sensemaking model shown in Figure 2).

#### **4. Application Context and Methodology**

In moving from the conceptual to the empirical, the process model will be tested and validated in the context of data analysis related to student recruitment in UK Higher Education (HE). This is a sector that has become increasingly competitive with the increase of student fees and the deregulation of student numbers. As a consequence, significant sensemaking effort is being expended on understanding what drives student choice in-and-around courses and institution for example. For those doing the analysis, the situation is ambiguous and equivocal – though a central data source is available (the Higher Education Information Database for Institution (HEIDI)), whether it covers the necessary data, how the data link in the context of specific questions and, indeed, what questions to ask are open. Further, HEIDI data is not currently in a shape or format that allows advanced analytics or visualization – so additional tools and data preparation are required.

Within this context, our aim is to empirically seed the model above by (automatically) monitoring how analysts in the HE sector go about their work and interact with the data and the analytical software. In doing this we adopt a Design Science Research (DSR) approach comprising of three iterations. Figure 4 illustrates an overall view of the DSR methodology in this research:

1. *First iteration (Infrastructure set-up).*

This iteration (completed) concentrates on extracting, transforming and loading HEIDI data into a new database in a manner suitable for advanced analytics and visualisation. Here, the technical sensemaking monitoring infrastructure is created, enabling the capture of analyst interaction with data through the chosen analytical software (Tableau).

2. *Second iteration (Analytical observation and interaction pattern mining).*

This iteration takes a clickstream approach to recording analysts' interactions with the analytical software. Here, we focus on applying suitable Data Mining (DM) techniques, interaction pattern mining, on the captured interactions in order to discover usage patterns/scenarios [9], [11]. These patterns along with the analysis objectives, discovered cues, developed hypothesis/hypotheses and concluded findings help in constructing and updating the computational Frame-of-Reference (FoR) each time the analyst/s perform new analysis tasks on the software, see Figure 3.

3. *Third iteration (Clustering sensemaking patterns using machine learning).*

In the third and last iteration, we aim to improve the frame of reference by utilising Machine Learning (ML) techniques in order to cluster the developed competing hypotheses into categories depending on the analysis objectives they fall under. Then, Analysis of Competing Hypotheses (ACH) [8], [13] will be applied to aid the judgment on the best developed hypothesis for the same analysis objective category – leading to update the computational frame of reference.

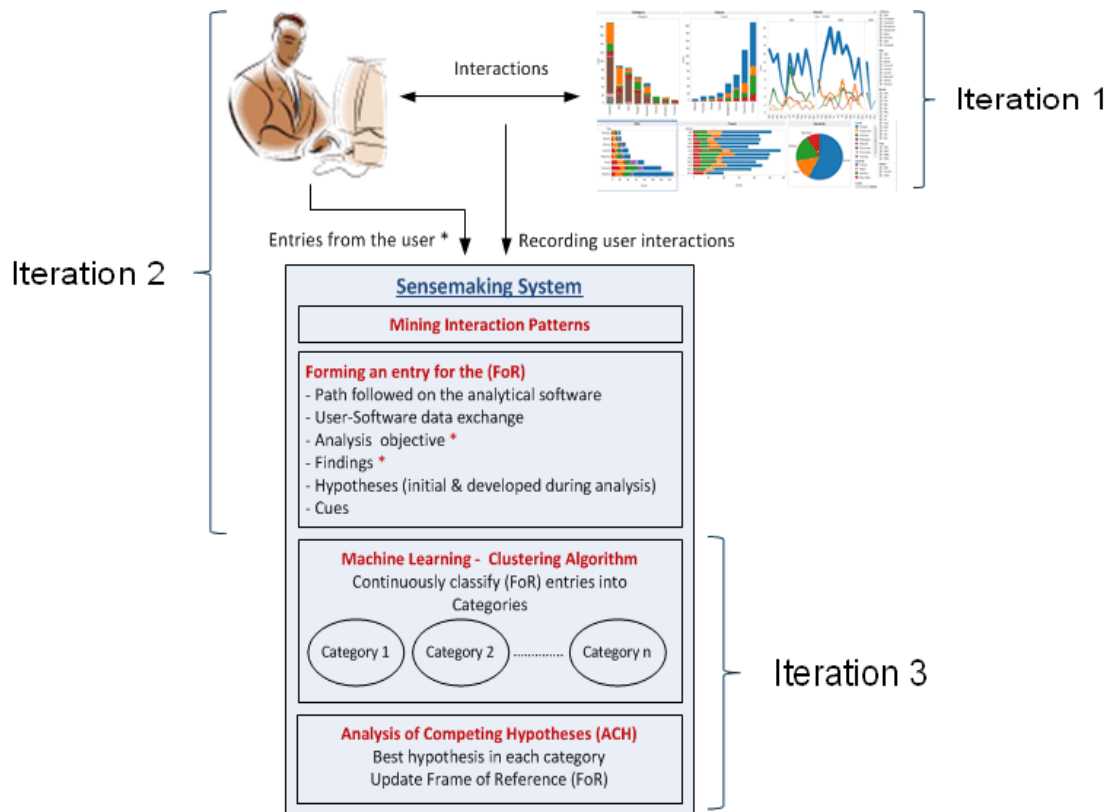


Fig 4. Methodology overview

## 5. Conclusion and Future Work

The importance of sensemaking in organisational decision-making stems from its role in understanding emerging equivocal and ambiguous situations (especially with a world of ever increasing data). This understanding is achieved through constructing or re-constructing Frames of Reference (FoR) that help in understanding the factors initiating the sensemaking processes of noticing, interpretation and action. The proposed framework for discovering sensemaking patterns during data analysis seeks to benefit from combining the powers of data mining and machine learning techniques and algorithms, applying them on user interactions with data analysis tools in order to discover usage patterns. These usage patterns represent the sensemaking journey the users go through until finding answers that are satisficing for the problem under investigation - in essence capturing a trail of analyst's naturalistic decision making processes. Over time, automated task monitoring will capture an audit trail of how data were brought together and used in relation to the analysis task, enabling a view on how the FoR is questioned, elaborated and reframed.

The proposed framework aims to preserve the analysis experience during the data analysis life cycle. Moreover, it offers a way to highlight the dominant usage pattern for a specific analysis objective and to find the percentage of the successful, unsuccessful and abandoned analysis tasks. Consequently, it intends to address the absence of a computational sensemaking framework that can be operationalised. We believe that addressing this gap is of importance to the research of sensemaking in organisations.

At this point, we have completed the first iteration of research and on-going research is twofold. First, to record and mine analyst interaction with their software tools in order to construct their frame(s) of reference. Second, we will utilize machine learning and analysis of competing hypothesis to cluster analysis objectives into categories and find the most satisfactory hypothesis in each category.



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