Embedded to Interpretive: A Paradigm Shift in Knowledge Discovery to Represent Dynamic Knowledge

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Abstract
This position paper purports a novel extension for knowledge extraction and interpretation by exploring the existence of knowledge via interdisciplinary routes. The existing knowledge discovery mindset operates in the embedded paradigm which encompasses the premise that knowledge is embedded in data and should be discovered. Hence, at present, data representation and computational approaches use structural properties of data to discover new knowledge. The limitation of this perspective is that it leads to finding a possible existence rather than possible knowledge within a context. As a solution, we propose a new perspective to knowledge discovery, the interpretive paradigm. In this approach, we argue that knowledge in its true definition is interactive, even though the structural properties play a significant role in data representation and transformation. Thus, knowledge is nonsensical in the existence of absolute nature. Knowledge is a construct by the existence of a schema of associated other constructs. Given this premise, data becomes a signal to an interpreter but not the interpretation itself. Hence, multiple interpretations can be accommodated from the same data depending on the schema that is used to interpret them. The knowledge of the interpretive paradigm is in constant evolution as it is constructed (as opposed to *mining* in the embedded paradigm) at the interaction of the signal and the interpreter. We believe that the proposed paradigm will bring a new perspective to knowledge discovery methods. This will enable systems to adopt diversified knowledge that is unique to a variety of representations of the knowledge the society, such as different stages of an individual, groups, cultures, and so on.

Keywords
Knowledge as a construct, data as signal, dynamic knowledge, interpretive paradigm, embedded paradigm

1. Introduction

Knowledge discovery is the process of manipulating a set of symbols representing a collection of propositions to produce a new representation of existing symbols. These symbols are concrete enough that we can manipulate them (move them around, take them apart, copy them, string

In A. Martin, K. Hinkelmann, H.-G. Fill, A. Gerber, D. Lenat, R. Stolle, F. van Harmelen (Eds.), Proceedings of the AAAI 2023 Spring Symposium on Challenges Requiring the Combination of Machine Learning and Knowledge Engineering (AAAI-MAKE 2023), Hyatt Regency, San Francisco Airport, California, USA, March 27-29, 2023.
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them together, and so on) in such a way to construct representations of new propositions [1]. For example, consider the two sentences *John loves Mary* and *Mary is coming to the party.* After manipulation, we can discover the new knowledge *John's love is attending to a party.* However, it is possible to obtain many different interpretations based on the technique used for manipulation such as Natural Language Processing (NLP). Hence, existing knowledge discovery methods operate in the embedded paradigm, where the assumption is that knowledge is embedded in data, and thus should be discovered.

Data is the fundamental unit of analysis in knowledge discovery. When a person purchases an item from a store, the transaction is recorded with a variety of data associated with the interaction such as customer's name, date of purchase, item purchased, quantity, and so on. This data later will be processed into information by way of labeling, summarizing, categorizing, or by other means. Then, knowledge is finally discovered as hidden dependencies and relationships [2]. At present, data representations and uncovering hidden structural properties through mathematical means define the basis of knowledge discovery [1], which is defined as the embedded paradigm for knowledge discovery. As per the embedded paradigm, something that has happened in the past should hold all the traces related to that occurrence. The limitation of the embedded paradigm is its assumption of discovering a possible existence over possible knowledge, thus hindering the evolution of knowledge.

In this position paper, we propose the *interpretive paradigm* for knowledge discovery. The interpretive paradigm proposes shifting from the absolute space of existence (as per the embedded paradigm) to knowledge construction via interactions. That is, we introduce the concept of knowledge construction over knowledge discovery. While this research is motivated by the recent work of Senaratne et al. [3, 4], we will bring an interdisciplinary perspective to the subject being discussed to inspire new approaches for Artificial Intelligence (AI) in constructing knowledge from the data we gather. In Section 3, we present the construction process of knowledge under the new paradigm as a framework, and a discussion lead by examples from a COVID-19 dataset, YAGO-4 and a visual representation in Section 4.

2. Related Work

A paradigm holds fundamental patterns that define the means of theorization, generalization, and experimentation, which supports a person to form the reality [5]. Hence, any attempt to explain the nature of knowledge, and how it comes to existence can also be related to many paradigms. In this section, we discuss the literature related to these different paradigms of knowledge and their representation from both psychology and computer science perspectives.

2.1. Knowledge Representation in Computer Science

Knowledge representation focuses on the study of the human mind. In computer science, all theories of AI are rooted in simulating how the human brain functions, how it stores facts and relationships, how it processes information, and how it engages with the external world [6]. However, knowledge representation and reasoning has long been recognized as an area of research in AI, due to the requirement of symbolically encoding human knowledge and reasoning in a way that this knowledge can be processed by a computer to act and think intelligently similar to a human [2].

Long before the advent of AI, mathematical logicians had developed the art of formalizing declarative knowledge. The mathematicians and statisticians were not focused on automating reasoning capabilities, but required a mechanism to normalize mathematics. In this light, mathematical logic, named first-order predicate logic and propositional logic were used as a means of representing declarative knowledge [6]. As symbolic logic defines the standard for generality and precision in computer systems, it was possible to design any computer system using logic [7]. However, with the advancement of technology, there arose the requirement of having a universal knowledge representation language that synergizes the expressive power of natural languages with the precision of symbolic logic, and most importantly, a mechanism to represent complex relationships among the entities of the real-world [7].

This gave the introduction to graph based knowledge representation. A graph represents knowledge as a collection of nodes and edges, where an edge exists between two nodes that hold a relationship. Due to the complexity of relationships, a variety of graph based structures were used to represent knowledge such as attributed graphs, and directed edge-labelled graphs as opposed to plain graphs [8]. After graph based knowledge representation, another structure for knowledge representation was introduced, named frames and scripts. They were introduced with the aim of provisioning voluminous characteristics of knowledge [9].

With the introduction of the semantic web, also named as Web 3.0, the need arose to have a web of data that is machine readable. Hence, Knowledge Graphs (KG) received the research focus as a suitable means of representing knowledge on the web. A KG is a new structure for knowledge representation on the semantic web. A Knowledge Graph based knowledge representation provides a denotational formal semantic, allows structured knowledge representation, allows to have computational properties assigned to knowledge, allows users to have control over the knowledge repository, and most importantly, allows storage of logical knowledge. That means, the knowledge in a KG should support inferencing [10]. KGs represent information about entities in the real-world in a structured form, together with relationships between the entities. Even though the term KG existed in the literature since mid 1900s, the announcement made by Google in 2012, followed by the adoption of KGs by other industrial giants such as Facebook and Amazon made KGs an area of interest for researchers [11].

In a KG, while a collection of facts and their interconnections based on structural properties of a graph are referenced as knowledge, whether a mere set of facts can be called as knowledge is questionable. However, to facilitate AI and machine learning tasks, existing knowledge representation techniques such as first-order logic, symbols, graphs, and frames all adopt structural means of embedding knowledge.

2.2. Embedded Paradigm of Knowledge

In general, knowledge discovery in the information system domain begins with data. When a person named *Bob* purchases a CPU, this transaction is recorded together with the data associated with the interaction, such as his name, date of purchase, price, and so on. As such, in any information system data is generated as a result of an interaction between entities such as person-person, person-object, and object-object. This data will be processed later to obtain information either by labeling, summarizing, categorizing, or by applying another data organization method [2]. The knowledge is finally seen as finding hidden dependencies and relationships [2]. At present, data representation and uncovering hidden structural properties through mathematical means define the basis of knowledge discovery. This approach of discovering knowledge is defined as the embedded paradigm of knowledge discovery.

The embedded paradigm assumes that knowledge is embedded in data [12, 2, 13]. On the retrospective grounds, something that has happened in the past should hold all the traces related to that occurrence. Thus, data is treated as an atomic unit that embodies universal meaning to that occurrence. Steps are later taken to build from those atomic units to construct the occurrence through deduction. This postulates the existence of knowledge with the data elements that should be mined (hence data mining) through structural investigations that include assessments such as weights, and arrangements such as KGs [14].

One limitation of this approach is that the occurrences are multifarious, and span through the abstract-concrete continuum. Hence, data that is captured in an interaction not necessarily originates from a finite space following distinct paths of realizations. In other words, an embedded approach sets a single convergent point of any aspect of knowledge it aims to recover. It also suggests *incompleteness* in relation to what could be uncovered, *dualism* in relation to what is uncovered, and true or false (or sometimes anomaly) *absoluteness* in relation to an absolute existence. Another limitation of the embedded paradigm is that it hinders evolution of knowledge. Hence, we propose shifting to the interpretive paradigm to overcome many of these limitations. The interpretive paradigm we propose, pioneers in this domain as none of the existing knowledge discovery techniques adopt the idea of dynamic knowledge construction.

3. Proposed Paradigm

Shifting from an absolute space of existence to knowledge construction via interactions is the key aspect of the proposed interpretive paradigm. To do so, it is imperative to bring the nature of the knowledge and its existence. This leads to obtaining a definition for knowledge. In the literature, knowledge is commonly defined as justified true belief. In the light of many critical reviews [15, 16], the definition we adopt for knowledge is; *the cognition of reality*. It is important to note that memory and knowledge are not used synonymously, but rather memory is instrumental in the context of knowledge.

3.1. Epistemology

Epistemologically, knowledge can hardly be associated with a single existence. Psychologists over the centuries have studied the epistemological development of humans from infants to adults to derive nature and justification of knowledge [17]. The assumption of the nature of knowledge (what and how it comes to existence) has defined the way it is approached and uncovered. This spectrum spans from *absolute* to *construct*. In this interpretive paradigm of knowledge, we bridge these epistemological developments of humans for the representation of knowledge in information systems and AI.

Humans develop a sense of understanding of the surrounding environment and the occurrences to decide on a possible interaction with the environment. This is achieved through schema development [18]. The sense of a set of statuses is interpreted based on the schema that gets activated at the time of the interaction. According to the theory of cognitive development [19], the translation into knowledge development levels can be either associated with an existing schema called assimilation, or accommodating into a new schema. In this, the existence of an object is interpreted with the existence of other associated existences. Thus, absolute existence is nonsensical as it is always either the person who interacts with it gives interpretations, or such an interpreter should be made available prior to the interaction. Hence, it is constructed in contrary to the notion of encapsulation in the embedded paradigm. When positioning the proposed paradigm, the next most probable argument will be about *data*, and what it represents. Data is considered as the status of a set of measurements we intend to capture, and data provides a signal for interpretations rather than the interpretations themselves.

3.2. Data as Signals

We consider data as recordings of the *statuses* of interactions. This means that various statuses are generated when an object interacts with another. In the real-world, this is common to all the man-made sensors where a sensor registers a change of status as data, or even to biological entities performing sensory interactions. This is what we refer to as *the world of interactions*. The world is constantly interacting with each other at the subatomic level to the abstract level (such as various thoughts held by people). However, all of these are meaningless, until they interact with an interpreter. What we as humans see is the result of the interpretations we provide to data, not what is registered in the retina. This is applicable for all other sensory receptions. Therefore, all stored data provides *signals* for an *interpreter*.

This does not negate the structural characteristics of data such as standard deviation, correlation, and the strength of associations. However, the knowledge is realized only when data interacts with an interpreter. Thus, data acts as a signal that activates certain states of an interpreter, through which the knowledge is constructed. We can explain the existing Knowledge Discovery (KD) methods using the proposed paradigm. For example, the training dataset used in training an Artificial Neural Network (ANN) develops an interpreter independent of the input, such that when data is received by the input layer, it acts as a signal to the interpreter. The same data when input to a differently trained ANN will produce a different output due to the difference in the interpreter.

As another example, consider simple data such as a series of temperature readings registered through a thermometer. This data obviously will carry structural properties that describe the distribution of the data in relation to other data. If a person with a schema of COVID-19 comes to interact with these temperature readings, this person would interpret the data in relation to COVID infections, while another with Dengue schema would interpret the data considering what is *normal* to his/her schema formed through the profession. However, if these recordings are CPU temperature recordings, what is normal would be totally different from the interpretations made by the COVID-19 or Dengue specialists.

Furthermore, it is natural for people to hold different interpretations for the same real-world instance. This is the reason for people to use phrases such as *I understand*, *I have the knowledge*, and so on. Similarly, when you as a reader study this paper, you will have different interpretations. This is because the words in the document act as data only to present a signal to the interpreter (your schema). The knowledge you gain, or the opinions you construct are the results of the signals (words) signaling and activating an interpreter (your mental schema). This is why knowledge is subjective to every individual and their subgroups, such as communities and fraternities. Though we believe that there is a shared knowledge or at least a schema, in reality, those schemas are also constructed and stored in both our declarative and non-declarative memory systems [20]. Thus, it will hardly be shared, but constructed in the same process of signal–interpreter interaction.

3.3. Capturing and Representation

Capturing of interactions will be registered as the changes in any form of sensing placed in the physical environment. For any capturing to occur, it must be in a physical form. Even an expressed opinion should be expressed either visually such as in writing or as a sketch, or auditory. The sensors we place for capturing these changes (or the oscillations) in the physical environment encompass the capturing phase. Once captured they will be represented in many forms. *Primary representations* would be in form of the changes recorded in the sensors. Temperature readings from a sensor or Global Positioning System (GPS) coordinates are examples of this nature. The other form of representation is the *Associated representation*. This representation is associated with an interpreter at the time of capturing. For instance, a hospital might record the symptoms of a patient as cough, fever, and so on, or an AI-based security camera may record the detection of a burglar. This kind of featured data is generated as a result of an interpreter. In the absence of the interpreter, the data will serve lesser strength for further interpretations. However, the representations of the latter are more associated with the extended interpretation of the ones that are used to represent data.

3.4. Signal Pool

For specific knowledge, all the available signals become the signal pool. It is not limited to a specific dataset. In the proposed paradigm, data is not considered as carriers of existence as it is assumed to be in the embedded counterpart, but instrumental in construction. The common practice in knowledge discovery is to consider a dataset for *discovering* knowledge. However, epistemologically knowledge construction observes a symbiotic relationship between data and interpreters. In other words, the choice of interpreter depends on the signal pool, and the signals used in the construction process depend on the active interpreters at the time of construction. For associated representations, the respective interpreters must be in place for the signal to exist. Thus, a signal pool may consists of many representations. In general, all the data that is captured and represented will act as signals at some point in generating knowledge.

3.5. Interpreter Pool and Knowledge Construction

As described before, mental schemas are the interpreters fundamentally occupied by humans to construct knowledge. The schema activation in memory [21] is progressive and hierarchical [20]. All schemas are interconnected through assimilation. These interconnections are hierarchical associations built in the semantic memory system, and a set of activations in the case of the non-declarative memory system such as priming [22]. Human learning is directly attributable

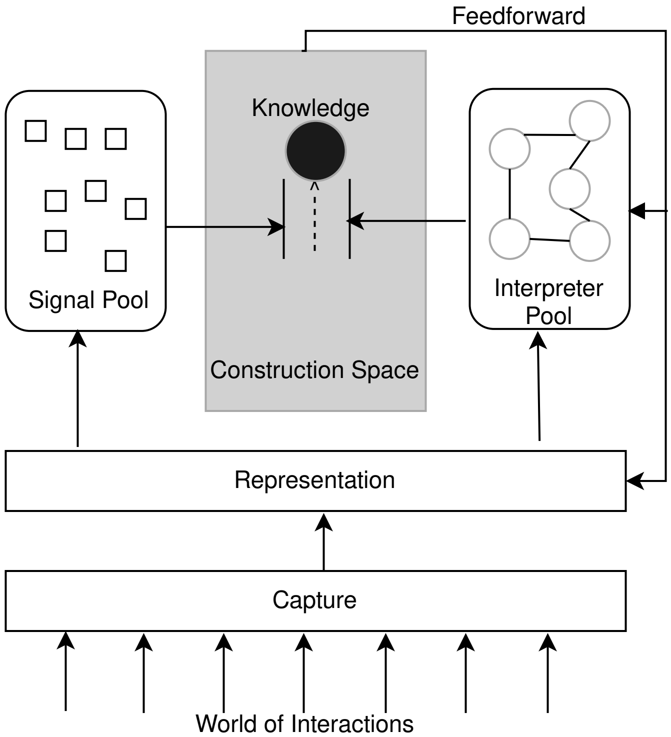

Figure 1: High-level representation of knowledge construction in the interpretive paradigm.

to the expansion of this interpreter pool by means of expanding and extending [23]. When a person is served with a cup of tea, the construction of the context-specific knowledge is based on multiple schemas such as type of tea, cup and saucer, nature of the drink, liquid nature of the serving, additional food items received, the person who serves the food, and so on. These interpreters are then validated through a variety of other constructions, and the more consistent the validation, the more confident humans become using those interpreters in the construction process. Any relative deviations, also called schema-discrepancy, that are also constructed through different interpreters will result in progressive updates to the interpreters [23]. Thus, the interpreter pool will be in constant evolution. The binding strength of the interpreters is dependent on the previous bindings that have occurred in the construction space.

Evolution and dynamic knowledge generation are very much integral to the interpretive paradigm. As knowledge is not regarded as absolute existence, what is always observed is dynamic in knowledge construction. This dynamism is associated with neither the signals nor the interpreters, but in the interaction of both signals and interpreters. When the same signal set is considered, different interpreters construct different knowledge. Furthermore, depending on the interaction with other signals, interpreters get expanded or extended. This will lead to construction of knowledge progressively that is different from the previous. This way, it is now possible to construct different perspectives that may be held by different entities or clusters such as societies and cultures, just by changing the interpreters accordingly.

Forgetting is also an important psychological phenomenon that inspires evolution in interpreters. With the constant updates to the interpreter pool, some schematic associations will be less strong [21] and thus, will not be activated in the knowledge construction stages. Furthermore, forgetting serves an important purpose. That is the reduction of associative-interference [24]. These interferences are mainly in two forms as proactive and retroactive. The former is the interference effects experienced with the past schema activations, and the latter is the interference of past schema activations due to newly constructed schemas. We propose to introduce forgetting in the interpreter pool by introducing suppressors that will keep the interpreter pool always changing and refreshing, rather than constant expansion. This prevents the single convergence of interpreter pool in the future.

The knowledge in the interpretive paradigm therefore should be constructed. Figure 1 shows a high-level architecture of a system that may enable the construction process of knowledge under the proposed paradigm. The data is the point of origin of everything, and data should be treated as the outcome of a variety of interactions that occur either in their natural or manifested setting. The world of interactions will be captured through sensors and represented through a variety of structural means similar to what is used in the present-day context. The signal pool imputes captured statuses as well as derived structural properties. The interpreter pool on the other hand comprises the cognitive schemas which will be activated during knowledge construction. These constructs will be re-captured and placed in a feed-forward loop as interpreters for future knowledge construction to enable knowledge evolution.

4. Interpretive Paradigm in Real-World Scenarios

Consider the COVID-19 dataset[1] that is made publicly available by the Israeli ministry of health. It contains data about individuals who were tested for COVID-19 [25]. The dataset contains information such as demographic information of people, symptoms, source of infection, symptoms onset date, and test result. To obtain a different representation of data, we could aggregate the records of all individuals who were tested for COVID-19 on a single day. That is, we can sum the counts under each attribute for a particular date to determine whether the counts occurring under each attribute is higher or lower than the average value (threshold) of the particular attribute. This provides insights on the increase or decrease of counts in comparison to a specific threshold. We can establish inter-relationships among these dates by connecting two consecutive days of the same week in chronological order. While the embedded paradigm considers these new findings as hidden knowledge, in the interpretive paradigm when these thresholds are interpreted with a COVID-19 schema, the threshold serves as a signal rather than knowledge.

As another example, consider the real-world Knowledge Graph YAGO-4[2]. It collects facts about instances from Wikidata, but it forces them into a rigorous type hierarchy with semantic constraints. The complex taxonomy of Wikidata is replaced by the simpler and clean taxonomy of schema.org. YAGO-4 has a well-defined notion of classes. For example, a *Person* is defined as a subclass of *Thing*, and has an explicit set of associated relations such as *dateofBirth*, *affiliation*, and so on. In contrast, other relations such as *capitalOf*, *headquarter* or *population* are not applicable

[1] https://data.gov.il/dataset/covid-19
[2] https://yago-knowledge.org/downloads/yago-4

to the instances of the class *Person*. This comprehensive principle of semantic consistency leads to several design choices [26]. A schema in a KG avoids possible misinterpretations of relations associated with entities. The schema ensures that an entity or relationship provides the same signal to every user. For example, the relation *affiliation* can provide different signals based on the entity with which it is associated. If associated with a person, an affiliation would refer to the organization the person is attached to, whereas an affiliation of a business would refer to a business partnership or a subsidiary.

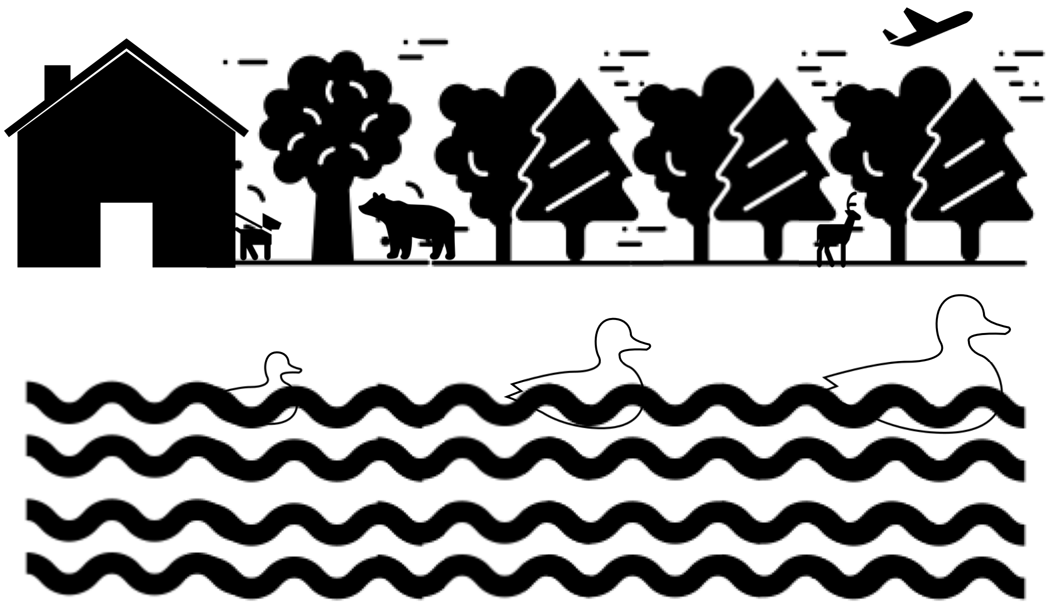

Figure 2: A scenery to elaborate the interpretive paradigm in graphical data. Source: authors' work.

In the embedded paradigm, one might say that a visualization fundamentally exhibits some sort of embedded knowledge. In contrary, the interpretive paradigm focuses on dynamic construction of knowledge. With reference to Figure 2, this picture only acts as a pool of signals. Every signal binds with an interpreter in constructing the knowledge. This includes a range of signals such as colors, shapes, and so on that represent the trees, animals, water way, and house. Depending on how these interpreters bind with the signals, knowledge gets constructed within a particular constructive space. The knowledge that gets constructed will be unique from one interpreter pool to another, hence the knowledge constructed is different from one person to another due to the variety in the interpreter pools of each person. Furthermore, each interpreter pool will construct knowledge within their respective interaction space, thus being independent from the interaction space of another interpreter pool. It is important to note that human memory is not a synonym for knowledge. The human memory is instrumental for the possession and expansion of the interpreter pool, thus bringing a new set of interpreters to the construction space in the successive interpretations.

5. Conclusion and Future Work

In an attempt to discover knowledge, it is important to understand the nature of the knowledge and in what paradigm the existence of such knowledge is considered. We argue that the approaches discussed in present knowledge discovery are in embedded paradigm, and that the knowledge is a construct that is constructed during the interaction of signals with an interpreter. This is what we propose as the the interpretive paradigm. We propose this paradigm as an extension, not a replacement, for the existing approaches adopted in knowledge discovery. While present approaches enhance the structural representation of data whilst improving the quality of the signal, the proposed interpretive paradigm will allow dynamic knowledge construction from the same dataset using a variety of sources such as humans as individuals, groups, societies, and ideologies. This will enable capturing evolution of knowledge.

It is our belief that the proposed paradigm will aid the current and future algorithms in extending the power AI has to understand and interpret the human world. This is important as the human knowledge is highly subjective to the interpreters. Current implementations such as personalization and recommendation systems can greatly benefit by the interpretive paradigm. As opposed to bringing an artificial intelligence that *knows* everything, it is the constant evolution that we propose. In the era of humanoids, aspects such as education, companionship and counseling can be revolutionized if AI can get into the *shoes of a human* through our proposed paradigm. This further can lead to an interesting inquiry of whether an animal is any less knowledgeable than humans? Since the world is a pool of signals where knowledge is constructed at the interactions, the proposed paradigm unveils new avenues of representing animals' knowledge whilst simulating various behaviors.

Knowledge representation in the interpretive paradigm warrants researchers to treat data as a pool of signals for interpreters. In other words, it is a necessity to have a proper representation of the interpreters. Hence as future work, we aim to develop a mechanism to capture and represent different mental schemas as interpreters to interact in the knowledge construction space. While the proposed paradigm enables dynamic knowledge construction, as future work, we also aim to research for multiple ways of constructing and utilizing the knowledge construction space.

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