2023 IEEE International Conference on Web Services (ICWS) | 979-8-3503-0485-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICWS60048.2023.00103

Empowering Generative AI with Knowledge Base 4.0: Towards Linking Analytical, Cognitive, and Generative Intelligence

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***Abstract*—Intelligence refers to the ability to acquire and apply knowledge and skills, which comprises three fundamental components, namely knowledge, experience, and creativity. Consequently, there exist three primary Artificial Intelligence (AI) systems, namely Analytical AI, Cognitive AI, and Generative AI. Analytical AI is primarily concerned with comprehending the data and transforming it into contextualized data and knowledge. On the other hand, Cognitive AI is centered on understanding experience and aims to annotate, enrich, and utilize the knowledge, to facilitate decision-making. Lastly, Generative AI delves into the neural mechanisms involved in creative thinking and problem-solving, with a focus on enhancing the process of acquiring and applying knowledge and skills. This paper presents Knowledge Base 4.0 as the backend data for AI engines, which allows for linking knowledge and experience to enable empowering generative AI. The objective is not only to facilitate generating new content (such as text and images) but also to generate new processes when/if needed. We present the architecture of Knowledge Base 4.0 and the design and development of data services that construct and maintain this robust Knowledge Base. Additionally, we provide use cases in various domains, including health, policing, banking, and education.**

***Index Terms*—Knowledge Base, Generative AI, Crowdsourcing, weak supervision, Business Processes Automation**

I. Introduction

The contemporary era is marked by the advent of generative Artificial Intelligence (AI). This technological innovation has the potential to enable the creation of systems capable of surpassing the mere identification of patterns in data. Such systems have the ability to generate new data, as well as new process models and instances, based on learned patterns. To understand the capabilities of Generative AI, we first need to understand the term intelligence, a complex construct that has been studied extensively across various fields, including psychology and neuroscience. In scientific terms, intelligence is defined as the ability to learn, reason, problem-solve, and adapt to new situations [1]. Being intelligent involves using cognitive processes, such as perception, memory, and attention, to understand and process data and knowledge. This ability is influenced by factors such as knowledge and experiences [2].

Let us define intelligence as the ability to acquire and apply knowledge and skills [3]. In this context, the concept of intelligence comprises three primary components: Knowledge, Experience, and Creativity. *Knowledge* refers to the information and skills that an individual has acquired through learning and practice. *Experience*, on the other hand, encompasses the various life events and situations that an individual has encountered and how they have responded to them. Experience can lead to the development of a set of best practices that can facilitate complex processes by enabling individuals to learn from past events and situations, adapt to changing circumstances, and develop effectively problem-solving strategies. A *Process* is defined as a set of interrelated activities that work together to achieve a specific goal or outcome. It involves a sequence of steps, tasks, or operations that are performed in a particular order to produce a desired result. In a business context, a *Business Process* [4] refers to a series of activities or steps that are designed to achieve a specific business objective [5]. *Creativity*, the third component of intelligence, focuses on the problem of improving how to acquire and apply knowledge and skills. In particular, creativity involves the ability to generate new content (such as text, images, and speech) as well as new processes when/if needed.

This accumulation of knowledge, experience, and creativity can enhance an individual's ability to navigate complex systems and optimize outcomes. Additionally, this accumulation can foster the development of intuitive decision-making abilities that are informed by past knowledge and experiences and are effective in contexts where analytical reasoning may be insufficient. A deeper understanding of intelligence can pave the way for innovations in the field of Artificial Intelligence (AI).

In particular, AI aims to develop intelligent systems that can perform tasks that typically require human intelligence, such as learning, reasoning, and decision-making. The components of human intelligence have influenced the development of AI systems, and there are three primary types of AI systems based on these components: Analytical AI, Cognitive AI, and Generative AI, which correspond to the Intelligence components: Knowledge, Experience, and Creativity, respectively.

Analytical AI is an AI system that focuses on the problem of understanding raw data (e.g., text, image, and speech), transforming it into contextualized data and knowledge, and

979-8-3503-0485-5/23/$31.00 ©2023 IEEE
DOI 10.1109/ICWS60048.2023.00103

facilitating finding patterns, insights, evidence, and facts from data. This system is commonly used in tasks such as data/pattern mining, rating, ranking, extraction, recognition, and anomaly detection, as well as in predictive analytics. In particular, analytical AI utilizes various techniques, including data/bigdata analytics, statistical analysis, machine learning, and deep learning algorithms, to process and analyze large amounts of data and extract meaningful insights [6].

Cognitive AI, on the other hand, focuses on understanding experience and utilizing knowledge for decision-making. This system aims to mimic human cognitive processes, including perception, memory, attention, and reasoning and aims to facilitate decision-making. Cognitive AI is used in various applications, including healthcare, finance, and education, where it can assist knowledge workers in those fields, e.g., in diagnosing diseases, predicting market trends, and personalizing learning experiences.

Generative AI investigates the neural mechanisms involved in creative thinking and problem-solving, aiming to generate new and useful content, ideas, solutions, and/or processes. This can be done by leveraging techniques such as deep learning, reinforcement learning, evolutionary algorithms, and fuzzy logic. Generative AI has found applications in several fields, such as art, music, and design, by helping to produce original and creative works. Nevertheless, the most significant potential for Generative AI lies in automating, and improving processes, particularly in business process management (BPM) [5].

In our previous work [7], we proposed the use of crowdsourcing services for mimicking the knowledge of domain experts in knowledge-intensive processes, and use this knowledge to build a new type of Knowledge Base, namely Knowledge Base 4.0 (KB 4.0), that can facilitate the auto-labelling of the data to be used in learning algorithms. In this paper, we propose the integration of KB 4.0 with Generative AI to offer significant potential for business process automation and improvement. The objective is not only to facilitate generating new content, such as text, images, and speech but also to generate new processes and activities. We present the architecture of KB 4.0 and the design and development of data services that construct and maintain this robust Knowledge Base. The main components of KB 4.0 include:

- Data Lake Services: designed to facilitate organizing the Big Data generated from a variety of sources, including social, open, private (personal/business), and Internet of Things (IoT) data islands.
- Knowledge Lake Services: designed to automatically transform the raw data stored in the Data Lake into contextualized data and knowledge, and form a large Knowledge Graph.
- Cognitive AI Services: designed to mimic the knowledge and experience of subject-matter experts, and use that to annotate the nodes and relationships of the Knowledge Graph, which was generated by Knowledge Lake services.
- Generative AI Services: designed for maintaining the knowledge graph over time by utilizing the graph data as input and generating new nodes and relationships based on the ever-changing, never-ending data.
- Cognitive Recommendation Services: designed for enhancing the stakeholders' reasoning and experience, providing personalized support for decision-making and choosing the best next steps.

The rest of the paper is organized as follows: In Sect. II we provide the background and related work. We present the system architecture in Sect. III. In Sect. IV, we present a motivating scenario and experiments before concluding the paper with remarks for future directions in Sect. V.

II. Related Work

A. Analytical AI

The primary goal of analytical AI is to extract meaningful insights from large datasets and facilitate decision-making processes. Researchers have employed various techniques, such as data/bigdata analytics, statistical analysis, machine learning, and deep learning algorithms, to analyze and process data. Analytical AI heavily relies on access to large amounts of data to generate meaningful insights and support decision-making processes. With the increasing volume of data from various sources, including sensors, social media, news, and user-generated content, organizations need a reliable and scalable way to store and manage this data [8]. This is where Data Lake comes in as a key technology for the backend of Analytical AI. Data Lake as a Service [9] introduced to address this challenge by providing a unified platform to access and analyze diverse datasets. Additionally, it enables efficient data integration and management, making it easier to organize and prepare data for analytical tasks. Complementary to this approach, Knowledge Lake as a Service [10] was introduced to automatically transform the raw data, stored in the Data Lake, to contextualized data and knowledge. In this context, Knowledge Lakes provide the backend for the Analytical AI aiming to automate extracting insights, patterns, and facts from the contextualized data and knowledge. The goal is to provide a comprehensive view of the data and generate accurate and meaningful insights.

The main categories of related work in analytical AI include: (i) Data Mining [11]: This involves discovering patterns, insights, and evidence from datasets. Data mining is one of the most critical tasks of analytical AI, and it has been used for tasks such as rating, ranking, extraction, recognition, and anomaly detection; (ii) Machine Learning [12]: This involves designing algorithms that can learn from data and make predictions or decisions based on that data. Machine learning is a subset of artificial intelligence and is widely used in analytical AI to analyze and process data; (iii) Deep Learning [13]: This is a type of machine learning that involves designing neural networks with multiple layers. Deep learning is used for tasks such as image recognition, speech recognition, and natural language processing; (iv) Statistical Analysis [14]: This involves using statistical models and methods to analyze data and extract insights from it. Statistical analysis is a critical component of analytical AI and is used to identify trends, correlations, and patterns in data; (v) Data/Bigdata Analytics [15]: This involves using specialized tools and techniques to analyze large datasets. Big data analytics is essential in analytical AI because it enables the processing and analysis of vast amounts of data, which would be impossible using traditional methods; and (vii) Predictive Analytics [16]: This involves using statistical and machine learning models to make predictions about future events or behaviours. Predictive analytics is widely used in analytical AI to forecast trends, identify potential risks, and improve decision-making processes.

B. Cognitive AI

State of the art in Cognitive AI involves developing systems that can mimic human cognitive processes to facilitate decision-making. The main goal here is to assist knowledge workers in knowledge-intensive processes in decision-making and choosing the best next steps. To achieve this goal, researchers have been working in various fields, including Human-Computer Interaction [17], Human-Sensing [18], natural language processing [19], computer vision [20], and machine learning. These technologies help Cognitive AI systems to understand and interpret human language, images, and other types of unstructured data to identify patterns and derive meaningful insights. Additionally, researchers are exploring ways to incorporate human-like reasoning processes into these systems, enabling them to make decisions based on complex sets of rules and knowledge.

Experience is a vital component of Cognitive AI, as it enables the system to understand and learn from past interactions with its environment. Similar to how human cognition is shaped by experiences and memories, Cognitive AI systems can use the experience to build learning models to facilitate decision-making. Machine Learning (ML) encompasses a broad range of algorithms that can improve automatically through experience [21]. Recent progress in ML has been driven by the availability of Big Data, i.e., the large amount of data generated on open, private, social, and Internet of Things (IoT) data islands [22]. However, the main challenge for learning algorithms is the Poor Quality of Data. Data labelling is the process of understanding the context around raw data and using labels to breathe meanings into the data, so that the ML model can learn from the contextualized labelled data. The main goal here is to provide ground truth data for ML models.

Labelling the data is challenging, and the current state of the art in Machine Learning relies on massive sets of hand-labelled training data. Hand-labelling is quite expensive and requires domain experts to breathe their knowledge into the data (in the form of labels) by spending time and moving through each information item in the data set. Transfer learning [23] tries to address this challenge by using models that are already trained and applying them to similar tasks. However, this approach cannot be generalized to all different tasks. To fill this gap, weak supervision approaches [24]–[26] recently focused on leveraging higher-level and/or noisier input from subject-matter experts, i.e., domain experts who have extensive knowledge and experience in a specific domain. An example could be a domain expert with 20+ years of experience in the field, such as a police investigator who is an expert in criminal investigations, a teacher who is an expert in identifying creative students, or a psychologist who is an expert in identifying patterns of mental health disorders.

C. Genrative AI

Generative AI refers to the development of algorithms and models capable of generating new data that resembles the characteristics of the training data. Examples include: (i) Text Generation: Generating human-like text using techniques such as GPT (Generative Pre-trained Transformer) [27] models and LSTM (Long Short-Term Memory) networks [28]. An example includes GPT-4[1] (Generative Pre-trained Transformer 4) developed by OpenAI[2]. (ii) Image Generation: Generating images using techniques such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) [29]. An example includes DALL-E[3] developed by OpenAI. (iii) Video Generation: Generating videos by extending the techniques used in image generation. An example includes StyleGAN[4] developed by Nvidia[5]. (iv) Speech Generation: Generating music using deep learning techniques such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [28]. An example includes VALL-E[6] developed by Microsoft. (v) 3D Model Generation: Generating 3D models of objects and scenes using techniques such as voxel-based modelling and implicit surface modelling. An example includes GANalyze[7] developed by researchers at MIT[8]. (vi) Game Content Generation: Generating game content such as levels, quests, and characters using techniques such as procedural generation and reinforcement learning. Examples may include Procedural Generation, Character Generation, Quest and Dialogue Generation, and Music and Sound Generation in games in real-time. (vii) Code Generation: Generating code automatically using techniques such as Natural Language Processing and Deep Learning. An example includes GitHub Copilot[9] developed by GitHub[10] and OpenAI.

The potential of generative AI extends beyond just generating new data, as it has the capability to revolutionise the processes in organizations and personal life, by offering process automation and improvement. For example, Generative AI can automate content creation tasks such as article writing, social media posts, and product descriptions. Or it can be used to identify patterns and anomalies in financial transactions, helping to detect and prevent fraud, or to automatically inspect

[1] https://openai.com/blog/chatgpt
[2] https://openai.com/
[3] https://openai.com/product/dall-e-2
[4] https://paperswithcode.com/method/stylegan
[5] https://www.nvidia.com/
[6] https://valle-demo.github.io/
[7] http://ganalyze.csail.mit.edu/
[8] https://www.mit.edu/
[9] https://github.com/features/copilot
[10] https://github.com/

and assess the quality of products, reducing the need for manual inspection. Generative AI can also automate customer service tasks, such as responding to common queries and handling routine tasks, freeing up human agents to handle more complex issues.

D. Knowledge Base

A Knowledge Base (KB) is traditionally defined as a human/machine-readable library of information about concepts such as a person, product, organization, service, and topic [30]. Such concepts can be organized into a taxonomy, instances for each concept, and relationships among the concepts [31]. A KB can focus on general knowledge (e.g., 'wikidata.org/', 'db-pedia.org/', and 'yago-knowledge.org/' that provides general knowledge about people, cities, countries, movies, and organizations) or can be domain-specific (e.g., METASPACE [32] which is a community-populated KB of spatial metabolomes in health and disease). Many KBs are interlinked to form the backbone of the Web of Linked Data [33] with the goal of evolving the Web into a global data space. Such a data space will enable data-centric and knowledge-intensive applications (e.g., personalization and recommendation, entity linking, deep Q&A, and semantic search) to be more intelligent. Google Knowledge Graph [34] is an example of this.

A KB can be manually created. WordNet, i.e., a large lexical database, is an example of a manually created KB. Recent advances in building KBs focused on automating the building of large KB's [35]. These approaches mainly use Information Extraction (IE) techniques and harnessing private/public knowledge sources to automatically identify instances for each concept (e.g., a named entity such as Barack Obama extracted from a textual data and assigned it to the concept Person) as well as the relationships among them (e.g., identify the relationship between Barack Obama, an instance of the concept Person, and the United States, an instance of the concept Country). Other related work put one step forward to building KBs automatically and automating the curation of large KBs. For example, in our previous work DataSynapse [10], [36], we offered a curation pipeline to extract, enrich, and annotate information items related to instances of concepts in KBs to facilitate understanding of the relationships among the instances of concepts. DataSynapse focuses on building a domain-specific KB to offer a machine-readable library of information about concepts related to the government budget. The approach extends the state-of-the-art in Weak Supervision [24], [37] by breathing domain-specific knowledge into learning pipelines.

III. Building Knowledge Base 4.0

The fourth industrial revolution, commonly known as Industry 4.0, is rapidly transforming the way businesses operate. With the advent of Artificial Intelligence (AI) and Machine Learning (ML), a new breed of data-centric and knowledge-intensive processes has emerged. In this context, capturing and utilizing the intelligence derived from these processes is critical for organizations to remain competitive. This requires empowering novice and inexperienced knowledge workers to benefit from AI-powered decision-making.

To address this need, we propose the Knowledge Base 4.0 architecture, which serves as the backend data for AI engines. This architecture enables linking knowledge and experience to enable generative AI, not just for generating new content (such as text and images) but also for generating new processes as needed. The importance of generative AI lies in its ability to create new nodes and relationships in the Knowledge Graph, which will lead to generating new insights and best practices by synthesizing existing knowledge and experience.

The Knowledge Base 4.0 (KB 4.0) architecture and its associated data services are designed to construct and maintain a robust knowledge base. This knowledge base serves as the foundation for generative AI and enables organizations to leverage their data assets for better decision-making. By harnessing the power of generative AI, organizations can unlock new opportunities for innovation and growth, paving the way for a more prosperous future.

Figure 1 illustrates the proposed framework for building Knowledge Base 4.0. In the following, we present the main component of the proposed framework.

A. Analytical AI Services

The transformation of raw data into contextualized data and knowledge is a crucial task in many applications of Artificial Intelligence (AI). One such AI system is Analytical AI, which specializes in understanding raw data and extracting meaningful insights from it. The design of Analytics AI services involves several stages, including data acquisition, preprocessing, feature extraction, model building, and evaluation. In the data acquisition stage, raw data is collected from various sources, such as databases, sensors, and social media. The preprocessing stage involves cleaning and transforming the data to ensure its quality and consistency. Feature extraction is the process of identifying relevant features or attributes from the data that can be used to train the model. The model-building stage involves selecting an appropriate algorithm or a combination of algorithms to process and analyze the data. This involves choosing the right machine learning or deep learning models that are best suited for the task at hand. Finally, the evaluation stage involves testing the model's performance and assessing its accuracy and efficiency.

To achieve the above-mentioned tasks, we use our previous work Data Lake as a service [9] and Knowledge Lake as a Service [10] to automate organizing, processing, and curating the big data generated on different islands of data from social, open, private and Internet of Things (IoT) data islands. In particular, the Data Lake will facilitate organizing, indexing and querying the big data and metadata. The knowledge lake will facilitate transforming the raw data into contextualized data and knowledge that is modelled and stored in a large graph called the Knwowledge Graph.

Knowledge Graph, is a large, semantically rich graph database that represents information and knowledge as a set of nodes and edges. The nodes in the graph represent entities or

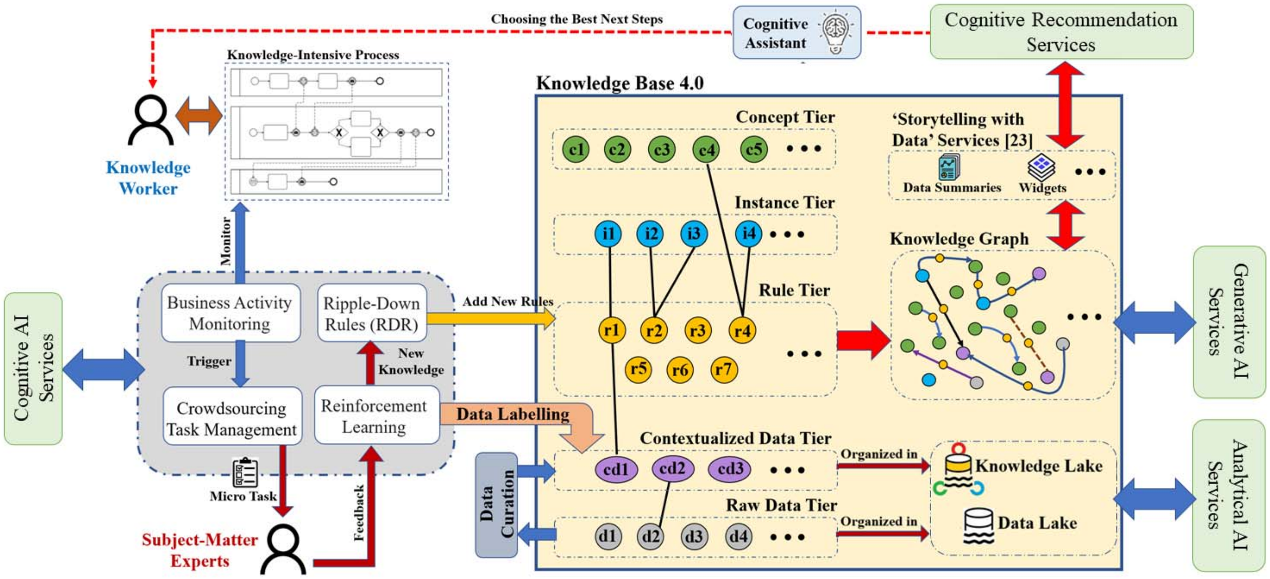

Fig. 1. Proposed framework for Generative AI-enabled Knowledge Base 4.0.

concepts, while the edges represent the relationships between these entities. The knowledge graph is used to store and manage contextualized data and knowledge extracted from the raw data using Analytical AI techniques. The Knowledge Graph is a powerful tool for representing and organizing knowledge in a structured and interconnected manner. It enables the system to link related concepts and entities together, facilitating reasoning and inference across different domains.

B. *Cognitive AI Services*

Cognitive AI services are utilized to mimic the knowledge of subject-matter experts and use that knowledge to annotate the Knowledge Graph using rule-based techniques. Cognitive AI is an AI system that focuses on understanding experience and utilizing knowledge for decision-making. It aims to understand human cognitive processes such as perception, memory, attention, and reasoning to facilitate decision-making. The Cognitive AI services can be designed to link the knowledge and expertise of subject-matter experts in a specific domains, such as healthcare, finance, and education. The system utilizes rule-based techniques to annotate the Knowledge Graph with contextualized information and knowledge, enabling the system to reason and infer across different domains.

The Cognitive AI services may utilize a variety of techniques, including natural language processing, knowledge representation, and reasoning, to extract knowledge and insights from unstructured data sources. The system then applies rule-based techniques to annotate the Knowledge Graph with the extracted knowledge, providing a rich and structured representation of the knowledge and expertise of subject-matter experts. In particular, the *Cognitive AI Services* component (Figure 1) contains the *Business Activity Monitoring* agent [38] which monitors business activities and can identify situations where a knowledge worker or a learning model has difficulties in choosing the best next steps. Examples may include handling cold start and concept drift situations.

This, in turn, will trigger the *Crowdsourcing Task Manager* service to generate a microtask and share that with subject-matter experts. The feedback provided by the experts will then feed into the *Reinforcement Learning* service, which may leverage state-of-the-art techniques, e.g., CrowdRL [39], to learn from subject-matter experts' feedback and use this knowledge for integrating task selection, task assignment and truth inference [40] together. This knowledge will be used to label the data automatically, and at the same time, will be fed into the *Ripple-Down Rules (RDR) [41]* component, which is an approach to building knowledge-based systems incrementally, while the KB is in routine use.

In particular, RDR is responsible for adding new rules to the *Rule Tier* in the Knowledge Base, where a rule r is accountable for identifying relationships among concepts, instances of the concepts, and information items (that are stored in *Raw Data Tier* and *Contextualized Data Tier*). The *Contextualized Data Tier* consists of: (i) Curated Data: curation process is responsible for transforming the raw data (stored in the Data Lake [9]) into contextualized data and knowledge (stored in the Knowledge Lake [10]). At this stage, our previous work [42] can be used to automate the curation process; and (ii) Labelled Data: recall that the *Reinforcement Learning service* component automates the labelling process based on the knowledge/feedback provided by the domain experts. The 'Data Labelling' arrow, in Figure 1, connects the Reinforcement Learning component to the Contextualized Data Tier, which will offer ML models to learn from the contextualized labelled data. This, in turn, will facilitate discovering deep insights that are trapped in the relationships among entities in the Knowledge Graph.

Rules may have different types. For example, in Figure 1: (i) rule $r4$ identified the relationship between concept $c4$ and instance $i4$; (ii) rule $r2$ identified the relationship between two instances $i2$ and $i3$; and (iii) rule $r1$ identified the relationship between instance $i1$ and information item $cd1$. Rules can be more complicated (similar to our previous work [42]) and identify the complex relationship among several concepts, instances, information items, and/or patterns in the data. The rule tier, illustrated in Figure 1, will facilitate the construction of the Knowledge Graph, which generates a graphical representation of the relationships among the data points in KB 4.0.

C. Generative AI Services

The Knowledge Graph, in Figure 1, is a valuable resource for organizations to capture and utilize intelligence, and Generative AI can play a significant role in maintaining this large graph over time. The main opportunity here is that the contextualized data and knowledge in the graph (i.e., the output of the Analytical AI component) are being annotated over time by the knowledge and experience of subject-matter experts (i.e., the output of the Cognitive AI component). This will offer the Generative AI component access to a rich source of information and focus on maintaining the Knowledge Graph by detecting and correcting errors and inconsistencies in the data, as well as expanding the graph by identifying new nodes and relationships.

This can be done by training generative AI models to recognize patterns and trends in the graph data and generate new nodes or relationships to fill gaps or correct inaccuracies. Several approaches, including graph neural networks (GNN) [43], generative adversarial networks (GANs) [44], and variational autoencoders (VAEs) [45] can be used to maintain the graph. For example, suppose the generative AI model identifies an incorrect relationship between two nodes or a missing data point. In that case, it can generate a new node or relationship to rectify the error. In addition, generative AI can help to expand the Knowledge Graph by identifying new concepts and activities to be added to the graph. For instance, if the generative AI model detects a new concept or entity related to an existing node in the graph, it can create a new node and/or relationship to incorporate the new information.

Moreover, generative AI can assist in improving the quality of the Knowledge Graph by continuously learning from the data and updating the graph accordingly. For example, the model can use reinforcement learning, where the Generative AI agent is trained to take actions that maximize a reward signal that is linked to the quality of the Knowledge Graph. The Generative AI agent can be presented with a set of candidate updates to the Knowledge Graph to choose which updates to apply based on the reward signal [46]. The reward signal could typically be defined based on the accuracy and completeness of the Knowledge Graph, as well as other metrics such as an analyst goal.

Finally, Generative AI Services can also be used to generate explanations for the decisions made by AI models [47]. For example, generative models can be used to generate natural language explanations for decisions made by a machine learning model [48]. These explanations can help users understand how the model arrived at its decision and provide insights into the underlying decision-making process. Furthermore, generative AI can be used to generate counterfactual explanations. These are explanations that describe how changing one or more input variables would have affected the model's output [49]. By generating counterfactual explanations, generative AI can help users understand how sensitive the model is to different inputs and provide insights into how the model can be improved.

D. Recommendation Services

In the age of Big Data and AI, the personalization of user experiences has become a significant factor in enhancing user satisfaction. Accordingly, we introduce a new layer on top of the Knowledge Graph to offer personalized services. To achieve this goal, the Storytelling with Data' [50] layer, illustrated in Figure 1, will: (i) provide services to generate data products [51] and data summaries; and (ii) provide a services layer to provide secure access to a cognitive assistant, similar to our previous work iCOP [52], [53], to assist knowledge workers in choosing the best next steps. The storytelling and summarization services will use data-driven, knowledge-driven, and cognition-driven approaches to understand user preferences, detect changes in user preferences over time, and predict unknown favourites. The detail of this approach has been presented in our previous work, Cognitive Recommender Systems [54].

In particular, Recommendation Services aims to provide personalized recommendations (e.g., a topic, product, or best practice) that cater to the unique needs of each user. The Recommendation Service can also utilize the user's historical data, preferences, and behaviour to suggest relevant tasks or activities based on their past interactions with the system. For example, suppose a user has previously shown an interest in a particular data or process. In that case, the recommendation service can suggest similar data, tasks or activities to the user in the future. This would enhance the user's experience and enable them to discover new tasks and activities they might not have encountered otherwise. Additionally, the recommendation service can optimize the user's workflow by suggesting the most efficient and effective sequence of tasks or activities based on their priorities, deadlines, and constraints. For instance, if the user needs to complete several tasks within a given timeframe, the recommendation service can suggest the order in which to complete the tasks based on their level of priority and dependencies. By personalizing the recommendations to the user's preferences and optimizing their workflow, cognitive recommender services can enhance user satisfaction and productivity. The potential applications of cognitive recommender services are vast and can have a significant impact on domains such as healthcare, finance, and education. The use of *Storytelling with Data* Services can be particularly beneficial for Cognitive AI services, as storytelling can enhance the accuracy and reliability of the insights generated by these services, leading to more informed decision-making and improved business outcomes.

IV. Motivating Scenario: From Augmentation to Automation

GitHub Copilot[11] is a powerful tool that uses generative AI to augment software engineers in their work, helping them to write more efficient and effective code. OpenAI used its state-of-the-art language model called GPT (Generative Pre-trained Transformer) to develop GitHub Copilot. Specifically, GitHub Copilot is built on GPT-3 (and recently updated to GPT-4), one of the most powerful natural language processing models developed by OpenAI, which was trained on a massive dataset of text from the Internet. This allows Copilot to generate code suggestions and even entire code snippets based on the context and intent of the user's input. With this technology, even novice programmers can quickly become proficient in their craft. A similar approach can be used in other fields (e.g., policing, health, banking, and education) to augment knowledge workers to be more productive. In particular, the use of generative AI in various processes has the potential to revolutionize the field, enabling novice knowledge workers to act like experienced workers and ultimately leading to more efficient and effective decision-making.

Our vision is to utilize KB 4.0 for the creation of domain-specific Co-pilots catering to knowledge workers operating in diverse domains such as health, banking, and education. Imagine a scenario where a novice police investigator is tasked with solving a complex case involving multiple suspects and a variety of potential leads. The investigator is overwhelmed and unsure of where to begin, lacking the experience and knowledge of a seasoned detective. This is where generative AI-enabled KB 4.0 can come into play. By analyzing data from previous investigations, annotated with the knowledge of experienced police investigators, the KB 4.0 system can generate potential leads and suggest courses of action for the investigator to follow. It can help to connect seemingly unrelated pieces of evidence, identify patterns and trends, and even predict the likelihood of a suspect being guilty. By leveraging the KB 4.0 technology, the The Cognitive Recommendation Services in the KB 4.0 system enables the new investigator to quickly gain the skills and knowledge needed to act like an experienced investigator. The Cognitive Assistant component can help to guide the investigation, providing the investigator with the necessary information and insights to make informed decisions and solve the case.

Let us consider another example in the education domain, where Generative AI can help new teachers identify creativity patterns and assist their students in becoming more creative. An Analytical AI approach, similar to our previous work [55], may use a rule-based approach for mining creative thinking patterns from big educational data. Complimentary to that, a Cognitive AI approach can mimic the knowledge of experienced teachers, e.g., using crowdsourcing services, to learn about effective strategies to promote creativity in their classroom. On top of these, the Generative AI component in KB 4.0 can then analyze this information and generate a set of lesson plans that incorporate these criteria in effective and creative ways. Over time, the KB 4.0 system will analyze student work and identify patterns of creativity. For example, the system might notice that certain students are particularly skilled at generating unique ideas, while others excel at developing those ideas into more complex projects. Armed with the cognitive assistant component in KB 4.0, the novice teacher can learn to offer a personalized approach to support each student's individual strengths and weaknesses, ultimately leading to a more creative and engaging classroom environment for everyone involved.

[11]https://github.com/features/copilot

Using Generative AI can go beyond process augmentation and offer process automation. For example, in one of our recent works [56], we put a step towards automating exam marking using the KB 4.0 technology. There are several benefits to automating exam marking using generative AI, as it will: (i) save time and resources, allowing educators to focus on other important tasks; (ii) eliminate human bias, ensuring all students are graded fairly and accurately; and (iii) provide immediate feedback to students, allowing them to learn from their mistakes and improve their performance in future exams. Another key benefit of using generative AI to automate exam marking is its ability to detect plagiarism. Furthermore, generative AI can detect subtle differences in writing styles, making it more difficult for students to evade detection. This will ensure academic integrity and discourage cheating, providing a fairer and more transparent evaluation of student performance. By automating the marking process, educators can focus on other important tasks, such as analyzing student performance data and developing personalized learning plans.

Generative AI can be used to help novice analysts in the fintech domain to act like experienced analysts, e.g., in identifying potential cases of money laundering, understanding customer journeys, and predicting customer churn. By analyzing large volumes of financial transaction data, generative AI models can enhance knowledge discovery from KB 4.0's Knowledge Graph to identify patterns and anomalies that may indicate suspicious activity. These patterns could include transactions involving large sums of money, transactions with unusual or inconsistent descriptions, or transactions involving high-risk individuals or entities. By analyzing customer data, generative AI models can identify patterns and trends that may indicate a customer is at risk of leaving. These patterns could include changes in spending behaviour, decreases in account activity, or changes in customer preferences. By using generative AI to analyze customer data, novice analysts can gain insights into customer behaviour that they may not have been able to identify otherwise. This can help them to make more informed decisions about how to retain customers and improve customer experience.

Generative AI can also be used in the healthcare domain to assist novice General Practitioners (GPs) to act like experienced ones. The KB 4.0 system can facilitate analysing the patient's symptoms, medical history, similar patients, drug side effects, and other data to generate a list of possible diagnoses. Additionally, generative AI can help novice GPs interpret medical images such as X-rays, CT scans, and MRIs. This can help the GP to make a more informed diagnosis and provide appropriate treatment to the patient.

V. Conclusion and Future Work

The integration of Knowledge Base 4.0 with Artificial Intelligence (AI) systems offers significant potential for process automation and improvement. KB 4.0 is a robust data repository that links knowledge and experience to empower Generative AI. We presented the architecture and development of data services for KB 4.0, which facilitates the generation of new content and processes. Generative AI, in particular, offers substantial benefits for business automation and improvement. By investigating neural mechanisms involved in creative thinking and problem-solving, Generative AI can identify novel approaches to acquiring and applying knowledge and skills. By utilizing KB 4.0, AI systems can effectively acquire and apply knowledge and skills, leading to improved problem-solving and decision-making capabilities.

As future work, We are investigation the effectiveness and efficiency of Generative AI systems powered by Knowledge Base 4.0 in various business domains, such as healthcare, finance, and education. We are extending the proposed architecture by developing neural mechanisms for Generative AI that can better mimic human cognitive processes, such as perception, attention, and reasoning. We are also developing systems that combine Generative AI with rule-based systems to enable more robust and explainable decision-making processes. Another future work is the exploration of the potential ethical and legal issues that may arise from the use of Generative AI and KB 4.0 in business automation and decision-making processes.

Acknowledgement

We acknowledge the Centre for Applied Artificial Intelligence at Macquarie University, Sydney, Australia for funding this research.

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