AI-Enhanced Database Management System

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Aims and Objectives

While databases are crucial to almost any business and its operations, users often need training, make mistakes, and may feel uncomfortable using a particular database, as databases are not all created equal nor are intuitively navigable and well-designed.

Arguably, the internet is a database, and the browser is a user interface to a database; while internet browsing has become intuitive, other databases and their interfaces are not. Designing a Database Management System (DBMS) that is intuitive to use and user-friendly may be challenging in specialised fields, i.e. healthcare.

Integrating an Artificial Intelligence aid into the user experience may limit and eliminate the user's interaction with newly created or poorly designed databases in the first place. A predefined set of instructions triggered by a written or dictated command from the user can help load, navigate, validate, visualise, and manipulate the data.

The solution is envisioned as a search field interface, allowing users to type or dictate queries in their natural language. These queries are then translated into instructions to be applied to multiple databases. As a result, the user does not have to interact directly with poorly designed or newly created databases.

Advanced solutions harnessing the power of machine learning are to be explored to automate the process while respecting the research's available time frame.

Contents:

1. Introduction:

Evidence shows that employees waste considerable time operating database systems for administrative and operational purposes. This avoidable inefficiency has a negative rippling effect on all industries, with very few exceptions. (Admin Matters: The Impact of NHS Administration on Patient Care, n.d.)

In a labour—and capital-intensive industry like healthcare, operational efficiency saves lives before money. Reducing administrative costs (time) means serving more patients without hiring more staff, increasing staff satisfaction, and saving money.

For example, doctors are not trained to use database systems as part of their educational curriculum. Even if software usage is included in the academic material, a new release or update may require new learning material and training. A newly hired doctor might want to extract patient information during a meeting in a hypothetical scenario. However, if the doctor cannot effortlessly/intuitively use the available database systems, the doctor and patient will suffer.

Well-designed database systems are intuitive to use. However, creating an intuitively navigable database that meets its inception purpose requires ingenuity, time, money, and all sorts of resources that are not readily available, especially in an industry like healthcare (NHS). This is evidenced by the data losses reported during the COVID-19 pandemic. (Kelion, 2020)

Designing an intuitive user interface requires a deep understanding of the intended user. This is not easily achieved when factoring in user perception to visual representation, pattern recognition, preferences, and other elements affecting the user experience while using a database.

This research will explore various Artificial Intelligence (AI) solutions/technologies and products to bridge the design and knowledge gap for general use cases. The focus is on harnessing AI capabilities to aid human-computer interaction (HCI) concerning databases. Aiming is to reach a point where a user interacts with databases intuitively, focusing only on the operational (billable) work and forgoing the administrative chores.

1.1. History of AI enhancements to Database systems

AI solutions in database management have been utilised on various levels for decades. Before the invention of Tone Dialling, human operators connected the phone lines manually after asking the user whom they wanted to speak with. Arguably, tone-dial technology was the

foundation of sound recognition, and a telephone switchboard is a database management system, with the operator acting as a Database Administrator (DBA).

Contemporary commercial application examples include chatbots, telephone directories (voice-activated), and other AI-collected and processed information, i.e., social media listeners. These applications have eliminated the need for a human operator to perform a highly predictable and automatable task, saving money and raising efficiency by reducing administrative workloads.

1.2. Current and Future of AI enhancements to Database systems

Emerging AI solutions for database management harnessing powerful AI tools are being commercialised to address the needs of a growing market with massive amounts of data that may benefit from a novel approach.

1952, Bell Labs created the first speech-recognition device (Audrey) to recognise spoken digits. Currently, one example of advancements in Natural Language Processing (NLP) is the commercialisation of AI voice assistants, which can understand many languages and perform complex tasks on behalf of the user.

The same NLP technology used to generate profit for technology giants like Apple, Google, and Amazon can eliminate some automatable tasks in most workplaces. By integrating an NLP to translate automatically and action the user's query/task in natural language, workloads are reduced and eliminated.

Examples of commercialised products that perform a similar task are Amazon Aurora, Oracle Digital Assistant, Microsoft Azure SQL Database, and others. However, the administrative time waste issue remains prevalent, whilst the available technology does not address the needs of a population that may seem unaware of the potential AI and NLP can bring to the workplace regarding HCI.

2. Literature review:

Professor Yannis Ioannidis said, “The database and HCI communities live on their separate islands with essentially no ferry line between them.” (Ioannidis, 1996) Academic material addressing this specific angle took much work to find. Nevertheless, searching by keyword has surfaced interesting material dating back to when the technology had not matured or reached today's levels by comparison. With much of the research being completed by the tech giants for profitability, the released technologies will have addressed many aspects of this research. However, the scientific material and software remain proprietary.

The primary search tool used to find the literature is Google Scholar, which generated results from reputable academic sources. However, the research also considered tech companies and potential users. The keywords used in the literature search process have multiple variations and combinations, but the core terms were NLP, ASR, AI, DBMS, and HCI.

2.1. Relevant published material

According to relevance to this research, the literature review material is selected and ordered in ascending order.

Natural language processing: an introduction (Nadkarni et al., 2011)

As a critical technology to be used in this research, a good starting point would be to understand the mechanics of NLP, its limitations, and set expectations.

The paper provides background information on how natural language processing evolved in the previous century, highlighting historical milestones and explaining the issues and solutions used. Different approaches and technologies work together to enable a computer to understand human natural language as input and react to it.

While the research dates to 2011, it has pointed out solutions and the logic behind them as an introduction to NLP, arguably contributing to the newer methods in use today (Neural Networks). While this is outdated by modern standards, it highlights the rapid progress in computer science within two decades. Nevertheless, the research is informative from reputable institutions with quality references.

As NLP matures, with open-source solutions available for use in this research (LangChain), understanding its capacity and abilities highlights an opportunity to research further audio-triggered commands actioned by nonhuman subjects.

Overall, the research is of high quality, mentioning technologies still in use or have arguably paved the way for more efficient solutions, like Neural networks, which were available and researched when this paper was published.

Literature Review on Automatic Speech Recognition (Ghai & Singh, 2012)

As a subfield of NLP, automatic speech recognition (ASR) is arguably the technology that enables the fastest way to communicate ideas with a computer until telekinesis is discovered.

The paper explains the multiple approaches and technologies used to correctly classify and convert human speech (voice) into text, detailing the differences between the applied solutions and speech processing stages and mentioning various tools.

The paper highlighted the limitations of developing an ASR system, considering factors like training materials, speed, accuracy, and linguistics, some of which are still present a decade after the research was published. It also mentioned many use cases of ASR related to the research being conducted.

The paper often mentions Neural Networks without properly explaining how and why they contribute to ASR. Thus, the functions performed by the neural network remain ambiguous, rendering it a “black box” solution to the problem.

The Integration of Artificial Intelligence into Database Systems (AI-DB Integration Review) (Austine et al., 2023)

This publication considers a broader aspect of AI's potential contribution to Databases, focusing on harnessing AI abilities to design and manage databases. AI can bring a new perspective to the designer, as AI may have an advantage in pattern recognition and through shared knowledge generated by a neural network.

According to the authors, “AI-powered DB” should be automatically scalable and optimised, which should improve database performance in terms of running queries and future-proofing a database from scalability difficulties.

The authors have addressed the HCI element of databases under the “Intelligent Database Interface (IDI)”, inexplicitly reaching a similar conclusion as per this research, where NLP is a possible solution to the HCI problems users face with Databases.

The paper considers many aspects AI can bring without thoroughly examining each avenue, which is predictable due to AI's seemingly endless potential. This renders the paper more of a review of AI potential in databases.

AI Meets Database: AI4DB and DB4AI (Li et al., 2021a)

The research examined the potential AI brings to Databases and vice versa. The research recognises that database management systems have evolved separately from AI, and some techniques can be exchanged to improve the performance of AI and Databases together and separately.

The research dives into the details of database management operations and how they can be improved by automating tasks and optimising queries through various machine-learning techniques. Furthermore, the paper highlighted the difficulties AI developers face when building AI, as the training process requires data to be governed with techniques found in database management systems.

The paper expands further in another version, “Database Meets Artificial Intelligence: A Survey,” which has even more details on how AI and databases can exchange benefits. While the research is well-detailed, it ignores the HCI element of databases and AI, focusing only on software performance-related challenges and forgoing the human element.

However, the improvements AI will bring to query processing will ultimately affect the user experience, assuming AI will be able to construct efficient queries from natural language input and will tune databases without human interference, thus reducing administrative time, as per this research’s goals.

The research is of the highest quality, as would be expected from computer science professors at highly prestigious universities. However, it is not easily read due to the jargon associated with advanced sciences that are very new and unheard of outside the industry.

XuanYuan: An AI-Native Database (Li et al., n.d.)

The research paper describes various tasks, challenges, and future expectations for DBMS and the DBA. It suggests various AI integration levels to solve the present and predicted issues for databases and database management systems. The author created five levels of AI integration within databases, each addressing functions and problems that are progressively more complicated—reaching a point of automation resembling machine awareness or science fiction.

The author examined current research and solutions relevant to the mentioned challenges and suggested a new DBMS, “XuanYuan”. An AI-native DBMS functions at "level 5" by the author's standards. No adequate explanation was provided on how it could be achieved.

The paper explained in detail many of the processes in a DBMS, which created expectations, some of which are being assessed. NLP integration discussed in this research would be level 1, per the authors' standards. The authors' suggestions all pointed to AI in general without mentioning the mechanics of how AI can perform a specific function, like designing, which would require a form of consciousness and purpose in AI unless prompted by a human.

The Architecture Of An Active Data Base Management System (McCarthy, n.d.)

The research paper investigates how an active DBMS should perform in its environment, focusing on the mechanics of how an active DBMS would react if certain conditions were met. Various complications were examined, and the most interesting was the nested transactions.

The paper describes the work of an ongoing project (HiPAC) designed to handle DBMS operations under a set of rules, “Event-Condition-Action” (ECA). Thus, decisions are made without a user prompt, following a preset logic in handling certain events.

The paper provides viable concepts for the ongoing NLP in DBMS research, as it demonstrates a system of processing predefined actions with predictable complications that will appear in this research at later stages. More specifically, accessing multiple databases and the complex queries dictated to the search bar would require a governing system that resembles the one described as an active DBMS.

Furthermore, a search function connected to multiple databases that take natural language as input is an active DBMS, taking advantage of what has been released following this research paper.

Considering the publishing date, the work that the author describes is now an integral part of many intelligent systems, including voice assistants like Alexa and Siri. These assistants can make many decisions in active time without user interference, raising privacy concerns regarding data collection and processing.

While the research may seem outdated, considering the simplicity of the working and publishing time, it explains how a DBMS can make decisions autonomously in active time. Considering the possible complications, data types, and decisions that could be made, it is no surprise that the HiPAC project is still ongoing.

The rise of artificial intelligence in healthcare applications (Bohr & Memarzadeh, 2020)

Following the initial example of healthcare, this research paper examines the applications and possible applications in the healthcare field specifically. With a broader overview of AI's effects on healthcare in general, the research examines the application of AI's contribution to genetics all the way to the subject's environment.

The paper lists possible applications for NLP in healthcare without expanding on the details. However, the applications mentioned can add value to this research as they underline other issues where NLP may assist decision-making besides reducing administrative workloads. An example would be NLP lie detection, which is ongoing research that should impact situations like drug-seeking behaviour in healthcare and general interactions with civil service.

The paper is a chapter in the book titled (Artificial Intelligence in Healthcare by Adam Bohr and Kaveh Memarzadeh), which serves as an introduction to the following chapters that are more detailed in AI applications. The authors are arguably healthcare experts with limited computer science knowledge. Thus, the paper should serve as a market study of AI-enhanced DBMS research.

Machine Learning for Databases (Li et al., 2021b)

The research paper describes the different types and levels of machine learning and their use case scenarios for databases. While machine learning is considered by many to be an important part of AI, machine learning is a broad term with sub-categories, each with a different use case.

As the authors describe, machine learning applications may seem distant from HCI but will ultimately cascade down to the user experience and interaction with the database. This is

confirmed by the previously reviewed research by the same authors regarding AI in databases (AI4DB and DB4AI).

While the authors are experts in the field, the language used can be difficult to decipher, which is expected considering the complexity of the subject. They have provided advanced use cases that emerged recently in the market by tech giants like Google, with the newly released database systems that utilise generative AI as part of their functions, i.e. (Google's AlloyDB AI).

2.2. Literature findings and conclusion:

Finding scientific literature on the subject was challenging because companies hold proprietary rights over scientific research and the tools needed to achieve the project goals. While the proposal may be reinventing the wheel compared to the number of products performing virtually similar functions, going into detail should prove otherwise on many levels or show the unique selling point of the project in hand.

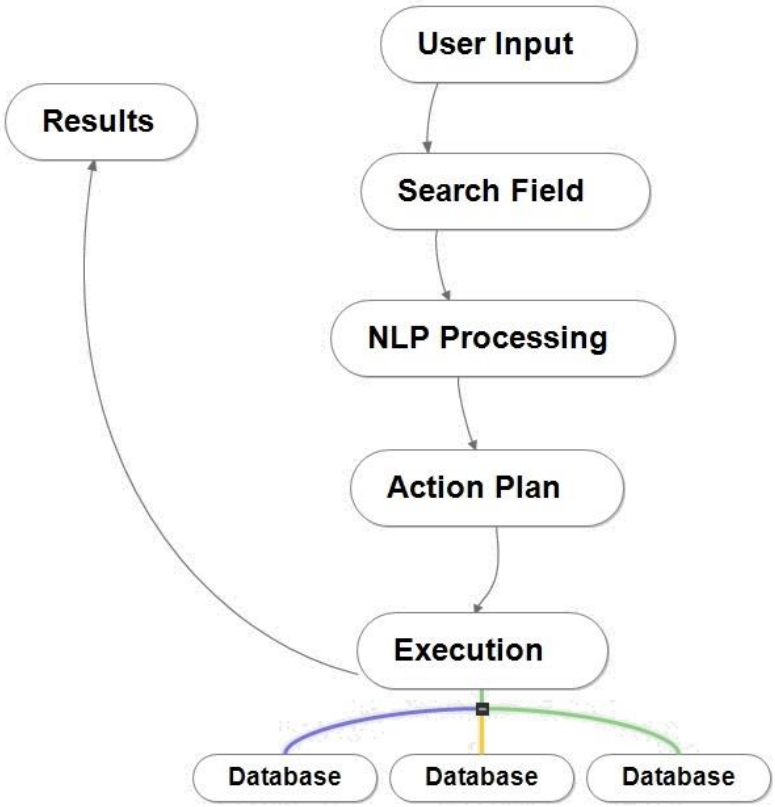
However, the literature found was enlightening. The possible applications and areas of AI that can enhance databases seem infinite. Meanwhile, the DBMS HCI element is widely ignored outside of commercial space. An example would be harnessing the power of Google Voice Assistant, Siri, or Alexa in a working environment. A hypothetical example would be a doctor making the rounds and speaking with patients, does not have to go back to log the interactions nor the observations as they are processed in the background in real-time, with less room for human error.

The research papers examined demonstrate the progress made in the relevant fields of the ongoing research while highlighting the need and potential for utilising these technologies in various scenarios to raise efficiency in most industries. While healthcare has been repeatedly mentioned and researched in this paper, it is the most appropriate example, while actual use cases extend beyond healthcare.

3. **Proposal:**

The user interface shall be a search bar with space to type or dictate a query in natural language.

The following diagram should demonstrate the data flow and functions of the search bar interface:



The initial phase will focus on linking an NLP tool (LangChain) to a search interface, which is then linked to sample databases.

Google Colab is a suitable environment for building the software, with LangChain acting as an NLP tool. Free-to-use datasets from Kaggle may act as databases after being converted to SQL using a tool like (Pandas).

The second phase will start after running successful queries in typed natural language. Free-to-use ASR tools will be tested for accuracy before making a final selection.

With respect to the available time frame, sophisticated tools harnessing newer and advanced methods (machine learning, other than speech audio analyses) are to be tested.

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