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CONNECT.ME: A STEP TOWARDS HYBRID INTELLIGENCE

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ABSTRACT: Artificial Intelligence (AI) is drastically transforming the world around us. Rather than replacing humans, hybrid intelligence combines human and machine intelligence to leverage each of their individual strengths. We summarize different requirements and approaches identified to achieve hybrid intelligence and focus on conversational AI to build a cognitive agent that supports knowledge management within an organization. The agent automatically extracts knowledge from artifacts provided or published by the users. In addition, the knowledge base steadily grows while the agent talks to the users and the users provide feedback and the system is continuously learning to extract new types of entities and relations to answer more questions based on the knowledge graph and to access other sources of information. The first types of entities and relations extracted already support users in finding colleagues with relevant skills or interests. Based on information provided by the agent, collaboration among employees and, thus, knowledge sharing and transfer is encouraged. The collaboration between the cognitive agent as an AI artifact and employees combined with a system that learns and adapts while in use stressing explainability and trust in its answers entails a step towards hybrid intelligence.

Keywords: *Hybrid Intelligence; Conversational AI; Knowledge Management; Collaboration*

1. PURPOSE OF THE PAPER

Who is the right colleague to ask about a specific issue? How do I find interested colleagues with the right skills to join a team and collaborate on a project? Unless you know all your colleagues in person, these seemingly simple questions are often hard to answer and require intensive search. However, much of the knowledge needed to connect to other colleagues is available within our brains and documents.

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Gaining access to implicit knowledge to foster knowledge exchange and transfer is a key knowledge management task (Probst et al., 2000). Especially when employees are retiring or leaving an organization, it is crucial to prevent brain drain (Hofer-Alfeis, 2008). Specifically, supporting employees to find colleagues with relevant skills and interests and connect with them is a simple form of knowledge management because it encourages collaboration and, thus, knowledge exchange. Yet, externalizing implicit knowledge through interviews and debriefings (Hofer-Alfeis, 2008; Ayele & Jonathan, 2018) is tedious and time-consuming. Therefore, it is often the bottleneck hindering successful knowledge management.

This paper aims to illustrate how cognitive agents grounded on continuously enhanced knowledge graphs constructed based on state-of-the-art AI solutions and appropriate feedback mechanisms for quality assurance can be used to support organization and domain-specific knowledge management. In addition, a first use case indicates how this approach helps users find the right colleagues and fosters collaboration. It thus serves very well as a foundation and is a step towards hybrid intelligence.

2. RELATED WORK

Hybrid intelligence is achieved by combining human intelligence and artificial (machine) intelligence to achieve a level of intelligence concerning problem-solving and decision-making that is out of reach for either one intelligence alone (Akata et al., 2020). The authors identify collaboration, adaptability, responsibility, and explainability as the key research challenges in achieving hybrid intelligence and discuss the respective state-of-the-art and open issues (Akata et al., 2020).

Unless we face a super intelligence that pursues its own goals, we may focus on two types of collaboration: supportive and participatory (Cummings et al., 2021). The most common type is supporting humans by weak AI systems that solve well-defined specific tasks. In participatory solutions, the AI system (agent) integrates into a team and acts as a teammate. This requires an interface for human-computer interaction based either on natural language or other forms of communication. However, supportive AI systems may also benefit from natural language interfaces.

AI systems with a natural language interface are called cognitive or conversational agents, assistants, or chatbots. Yet, while the primary purpose of a chatbot may be considered to just chat, cognitive agents are assumed to pursue or solve a specific task for their users either because they are asked to, or they decide to do so based on their perception of the environment. More generally, from an AI perspective, we are dealing with conversational AI (Kulkarni et al., 2019; McTear, 2020).

The application of big language models has vastly pushed the limits of natural language understanding and generation and achieved impressive successes. For example, the models of the GPT-family (Brown et al., 2020) or the OPT-family (Zhang et al., 2022) with their transformers and attention mechanisms appear to produce reasonable answers to arbitrary questions in natural language. Are these models ready to serve as end-to-end solutions for conversational agents? Are they the solution to our problem at hand?

The results are impressive: They sound good and are hard to tell apart from human answers (Brown et al., 2020, Zhang et al., 2022, Thoppilan et al., 2022). At a closer look, however, some cases reveal that there does not seem to be proper human-level understanding, and some answers provided are neither correct nor consistent with the context provided or with previous answers. Hence, we do not want to rely on these answers in most business situations. Furthermore, accessing the source of the information or some explanation from a large language model is not very straightforward.

A remedy to this problem is grounding conversational AI on knowledge bases—be them general and publicly accessible or domain-specific and private (Dinan et al., 2018; Chaudhuri et al., 2021; Fu et al., 2022). We will follow an approach based on an organization and domain-specific knowledge graph to support knowledge management.

3. APPROACH

In this section, we provide a detailed description of our approach. Figure 1 shows the main components of our cognitive agent within the application domain (López-Cózar et al., 2014). As grounding the cognitive agent on an organization and domain-specific knowledge graph is crucial to our approach, we first focus on the knowledge graph construction process. We then briefly describe the natural language processing (NLP) tasks (shown in blue) for understanding user intents, response generation, and extracting relevant knowledge from selected sources. We continue with a discussion of the dialogue and solution inference engines and the feedback mechanism to improve knowledge quality as another crucial part of our approach. Finally, we briefly sketch our first knowledge management use case that fosters employee collaboration. To lower the barrier of using the cognitive agent, it is integrated as a bot in a messaging client that is used organization-wide.

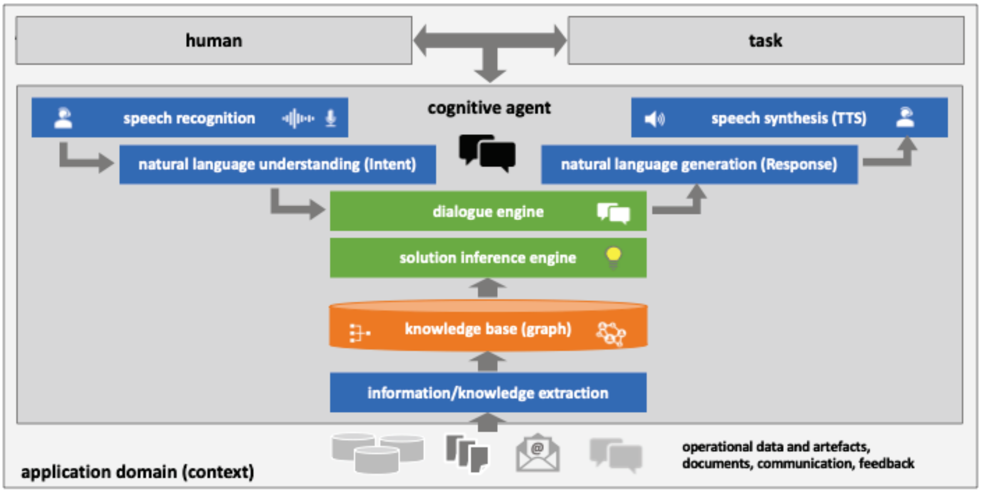

Figure 1. Main components of our cognitive agent and their interactions (based on López-Cózar et al., 2014).

3.1 Knowledge Graph Construction

The knowledge graph is the key component that stores and manages the externalized knowledge and, thus, the basis for answering any questions. There are two extreme ends to constructing knowledge graphs from data (Zhao et al., 2018): The top-down approach first defines an ontology consisting of schemata describing all relevant entity types and relation types. Subsequently, a knowledge graph is filled with entities and relations of the respective types extracted from relevant sources. By contrast, the bottom-up approach first extracts entities and relations as untyped objects and tries to identify appropriate types and structures in a follow-up step.

Initial experiments proved both extreme approaches to be infeasible for our application: Modelling an entire ontology upfront and ex-post integration and structuring of entities and relations are both very tedious and time-consuming. Furthermore, which entity types and relation types will be needed later at project kick-off is often unknown. There are parallels to data warehousing. A holistic modeling approach following the principles of Inmon (Inmon, 2005) is desirable but often infeasible in practice. By contrast, the approach following Kimball (Kimball & Ross, 2013) may have a higher risk of failing concerning schema integration. Hybrid strategies following the principle “think big, start small, grow step by step” are often successfully applied instead (SCN, 2013).

We follow this principle in our knowledge extracting and modeling process for constructing our domain and organization-specific knowledge graph, as shown in Figure 2. The goal is to create a fully typed knowledge graph with schemata for all relevant entities and relations. Rather than modeling the schemata upfront, they are iteratively identified and modeled. Thus, the knowledge graph is successively extended to cover entities and relations for further questions.

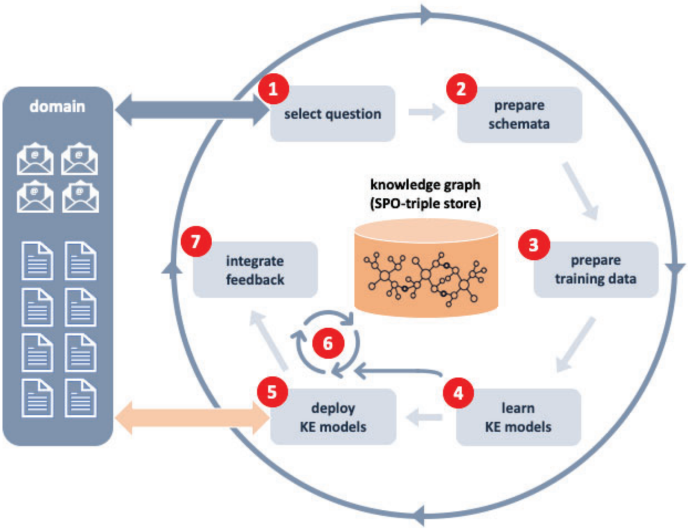

Figure 2. Iterative knowledge extraction and modeling process for constructing the knowledge graph.

In each iteration, a relevant question is selected (step 1), such as finding the right person to ask for an issue. Next, the entity and relation types required to answer the questions are identified and modeled appropriately (step 2). For any entity or relation type that does not already exist in the knowledge graph, a new knowledge extraction (KE) model must be constructed. This requires providing initial training data (step 3) and training or fine-tuning the model (step 4). Details regarding the NLP tasks involved in the KE models are described in the following section. The KE models are then deployed to extract entities and relations from existing data items (step 5). All KE models are continuously applied and monitored to extract entities and relations from new data items like ETL jobs in data warehousing (step 6). We assume that the extraction processes are error-prone and design the system to actively ask users for feedback based on confidence scores and deviations from expected content (step 7). The input is used to correct errors and fill missing values in the knowledge graph as part of the quality assurance loop. Finally, based on more and improved data, re-training of the KE models may be triggered (Shen et al., 2018). This allows early access to the results in any subsequent application and quick adaptation to changes in the data and the applications.

3.2 Natural Language Processing

Users may interact with the cognitive agent in written or spoken natural language. This requires several natural language processing (NLP) tasks to be addressed. For the sake of simplicity, we focus on text input and output. Standard pre-trained models for both text-to-speech recognition and speech synthesis work very well and will be added later. The remaining NLP tasks are understanding user intents, generating responses, and extracting knowledge from data sources in the knowledge graph construction process.

Given some examples for each intent, text classifiers to recognize intents can be fine-tuned based on pre-trained language models. The challenge is to define all relevant intents and trigger appropriate actions. The more intents that must be distinguished, the greater the risk of misunderstanding users. A feedback loop to assert correct understanding should be used to remedy this issue.

For specific intents that can be answered based on knowledge graph content, responses may be generated by following a set of rules. Natural language models conditioned on selected knowledge graph atoms may be used to get more response variability.

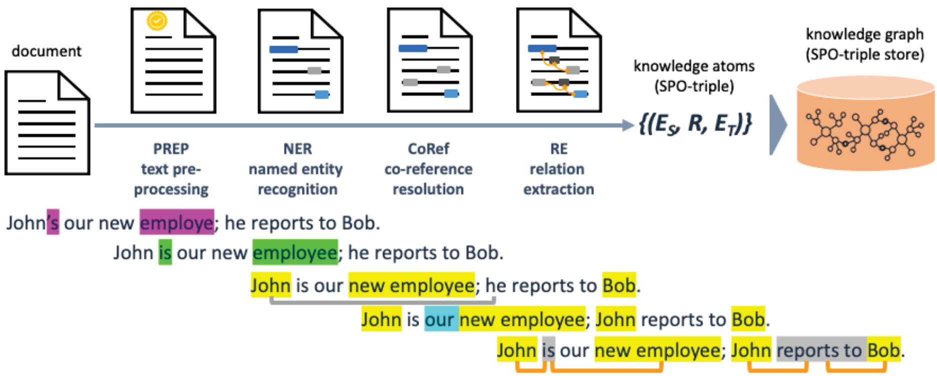

Figure 3. Knowledge extraction pipeline with relevant NLP tasks.

The knowledge extraction process heavily builds on different NLP tasks, as shown in Figure 3. Pre-trained models with fine-tuning for specific entities and relations are applied as described below. The goal of named entity recognition (NER) is to identify entities of a particular type, such as persons, locations, or organizations. For these generic entity types, numerous pre-trained models work well. However, fine-tuning to recognize domain-specific entities or adaption to specific entity types is required for domain-specific applications. The NER task is often tackled with deep learning approaches like bi-LSTM-networks or, more recently, with transformer-based networks in combination with a final conditional random field layer (Goyal et al., 2018; Panchendrarajan & Amaresan, 2018; Lothritz et al., 2020). Entity linking merges different entities if they refer to the same real-world object. Next, co-reference resolution (Co-Ref) attempts to substitute referencing words with the words they refer to. A well-known set of approaches mention pair models (Ng, 2017). Relation extraction (RE) identifies relevant relations between two entities. For this task, there are also well-known recurrent deep neural networks (Wang et al., 2021). All objects extracted are annotated with appropriate metadata such as recognition confidence, extraction timestamp, and source to enable quality assurance with user feedback.

3.3 Dialog and Solution Inference Engine

We follow the approach to ground the answers of the cognitive agent on knowledge bases to ensure more trustable and explainable responses. The primary source of information is the organization and domain-specific knowledge graph described above. Note, however, that it is not meant to be or remain the only source on which the cognitive agent is grounded. The solution inference engine may access different sources in a cascading schema of trust and decide if and how an answer is provided. As the initial agent is very limited in its abilities, it will tell its users if it cannot answer a question or lacks the required skill. Requests that cannot be handled well must be logged and trigger adaptation of the agent.

The dialogue engine glues together the communication with the users according to the perceived intents and context information provided and the solution inference mechanism. We currently use plain policy-based dialogue flows without the ability to learn conversation strategies. In addition to the communication triggered by users, the dialogue engine can initiate a conversation by itself to ask for feedback (see below).

3.4 Human in the Loop Feedback Mechanism

Typical usage scenarios of cognitive agents follow a pull strategy. Abstractly, users have an information need which they utter towards the agent. The agent recognizes the intent (NLU) in combination with context information, infers the answer, and creates a response. More advanced usage scenarios also have push strategies. On the one hand, this is relevant when the agent senses from the environment that a user needs help. On the other hand, we implement a feedback mechanism to engage the human in the loop to provide feedback. The agent keeps backlogs of entities and relations that should be checked. To create the backlog, each relevant object is assigned a quality score based on the recognition confidence of the knowledge extraction model, the age respectively last seen timestamp or the last queried timestamps, and the source. In addition, we plan to reduce any object's quality score in case appropriate anomaly detection or relation prediction methods flag the values observed as being suspicious. For entries in these backlogs, the agent actively requests user feedback used for quality assurance as described above. The KE models from the knowledge graph contraction process are reused to extract entities, relations, or attribute values uttered by users. Objects with a quality score below a predefined threshold are automatically put in their respective backlog at regular intervals. The dialog engine chooses items from the backlog based on the quality scores and specific users available for feedback at a given time. Finally, the quality is updated based on user feedback and may be removed from the backlog if the updated score is sufficiently large.

3.5 Knowledge Management Use Cases

The entire approach supports knowledge management by automatically extracting entities and relations stored to externalize implicit knowledge. In general, externalized knowledge is being used by the cognitive agent as a knowledge base to answer user queries. The content will also be used as input to other classical knowledge management approaches like expert interviews or debriefings.

The first selected question in the knowledge graph construction process focused on whom to ask for a specific issue. To answer this question, we extracted employees and their skills and interests from any available documents. First queries could be successfully answered based on similarity scores between the search phrases and the first knowledge atoms extracted. While the first results are promising, more content must be extracted and curated based on the quality assurance mechanism before an in-depth evaluation of the systems' capability to support further knowledge management tasks can be conducted.

Being able to recommend colleagues for specific issues or tasks is already a benefit. Even though a straightforward one, we already have an indirect form of knowledge transfer at this point. More importantly, direct knowledge transfer through collaboration among employees is encouraged by actively trying to connect them.

4. FINDINGS

When building organization and domain-specific cognitive agents, integrating individually constructed knowledge graphs helps provide an adaptive, explainable, and trustable solution. Especially for the latter, actively involving users to provide feedback is crucial to establish quality assurance with humans in the loop. Since both the vanilla top-down and bottom-up approaches to knowledge graph construction did not prove feasible, following the principle adopted from data warehousing to start small and grow step by step is also beneficial in our context. Addressing the problem of finding the right colleague for a given issue or joining a team enables direct knowledge transfer through collaboration and indirect knowledge transfer by externalizing formerly implicit knowledge in the knowledge graph.

5. RESEARCH IMPLICATIONS

The approach presented is only a first step towards hybrid intelligence and serves as an initial proof of concept on integrating and benefiting from cognitive agents, knowledge management, and humans in the loop for gaining feedback. However, bringing the right people together to solve single tasks or to form teams is a crucial challenge in organizations where not all members know each other in person. To achieve higher levels of hybrid intelligence, the agent will have to learn more skills such as accessing and providing context-specific information from different internal and external sources and, for example, actively participating in discussions or collecting current status information in daily project meetings. First, however, our focus is on extracting additional types of entities and relations as part of the iterative knowledge extraction and modeling process to support knowledge transfer among employees in an organization.

6. VALUE OF THE PAPER

We have presented a framework that indicates that the combination and orchestration of state-of-the-art NLP approaches together with explicit knowledge capture and appropriate actively triggered user feedback for quality assurance and data augmentation allows the construction of a domain-specific knowledge base on which cognitive agents should be grounded to provide more trustable and explainable answers.

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AUTHOR CONTRIBUTIONS

Both authors have contributed equally to the research and writing of the paper.

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