Natural Language Search using Calibrated Quantum Mesh

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Abstract—This paper describes the application of a search system for helping users find the most relevant answers to their questions from a set of documents. The system is developed based on a new algorithm for Natural Language Understanding (NLU) called Calibrated Quantum Mesh (CQM). CQM finds the right answers instead of documents. It also has the potential to resolve confusing and ambiguous cases by mimicking the way a human brain functions. The method has been evaluated on a set of queries provided by users. The relevant answers given by the Coseer search system has been judged by a human as well as compared to the answers given by a reliable answering system called AskCFPB. Coseer performed better in 57.0% cases, and worse in 16.5% cases, while the results were comparable to AskCFPB in 26.6% cases. The usefulness of a cognitive computing system over a Microsoft-powered key-word based search system is discussed. This is a small step toward enabling artificial intelligence to interact with users in a natural manner.

Keywords—chatbot, cognitive computing, natural language processing, NLP, cognitive search, NLU, natural language understanding

I. INTRODUCTION

Natural Language Search, and one of its prominent applications, Chatbots, are popular topics in the field of technology as well as research.

Their popularity can be attributed to the tremendous potential and promises in several fields. [1-6] There are several areas of business, for example, brand-building, customer acquisition, product discovery, support etc. that require human interaction. There is always high cost related to human labor, inaccuracy related to fatigue and general human biases and errors. An automation system based on Natural Language Search can remove several of these problems by simply replacing the human.

A well designed chatbot, for example, can be used to facilitate the internal processes of a business. A chatbot, if successfully developed as a subject matter expert, can be deployed to any part of the business so that any employee or customer can retrieve important information from it at any time.

However, at the current state of art, a clear majority of systems based on NLU are not well designed or accurate enough. A high accuracy is necessary so that business managers can entrust them with mission-critical roles and tasks.

Highly advanced Artificial Intelligence (AI) technologies like deep learning have been tremendously successful in analyzing structured data. [7-9] However, when it comes to unstructured data, especially processing natural language like English, they seem to fail. For a technology like deep learning to be successful, it needs a huge amount of training data which might not be available to the enterprises. Moreover, such data must be annotated by subject matter experts, which can be prohibitively expensive.

Most intelligent natural language systems like Chatbots fail because they are unable to interact and process content like human beings do. Frequently, they are based on keyword correlation which does not enable them to “understand” the relations between words and their context.

Humans process information around certain ideas. Ideas are entities that are expressed by words and phrases and complex relationships between them, – something computer systems cannot trivially handle. Thus, they are unable to retrieve meaning from information. Some essential characteristics of human thought process are: focusing on ideas rather than words, prioritizing ideas based on significance and credibility and knowing when there is not enough information available to take a decision.

Intelligent machines capable of producing high accuracy can be designed based on the imperatives mentioned above without relying on keywords. They can extract ideas, order them, store them in hierarchical data structure and even derive context from live conversations. This type of approach offers significant advantage over traditional chatbots in terms of capability and performance.

This unique paradigm of intelligent understanding of information is captured in one branch of AI technology: cognitive computing. [10-15] Cognitive computing can be used to automate tedious, repetitive and language-driven workflows that do not require human intelligence anymore. This would allow the humans to focus on creativity and judgment while the machines take care of the mundane jobs.

In this work, we have developed a Natural Language Search system that can help users with their queries. It analyzes the query placed by the user and suggests relevant answers from a list of Frequently Asked Questions (FAQ). The reported answer may be a direct match with an existing entry in FAQ or produce an answer that is part of some other entry.

To evaluate the performance of the system, we used a human judge as well as compared the results with that of AskCFPB. [16] AskCFPB is a well-established and trustworthy resource to get answers maintained by the Consumer Finance Protection Bureau of United States Government. It covers a variety of topics including bank accounts, credit reports, credit scores, debt collection, student loans and mortgages. There is a search box on the website where the users can enter their queries and look at related questions and answers. This system is powered by popular Microsoft search engine – Bing.

II. METHODS

A. *Tactical Cognitive Computing*

All Coseer systems are built using Tactical Cognitive Computing (TCC). TCC is a programing paradigm with a focus on high accuracy, short training times and low cost. Tactical Cognitive Computing has been developed as a solution to traditional cognitive computing systems that are expensive and take years to implement.

To be called tactical a cognitive computing system must be highly accurate. While lower level accuracy has been accepted and even lauded in the consumer world, the businesses need highly reliable systems.

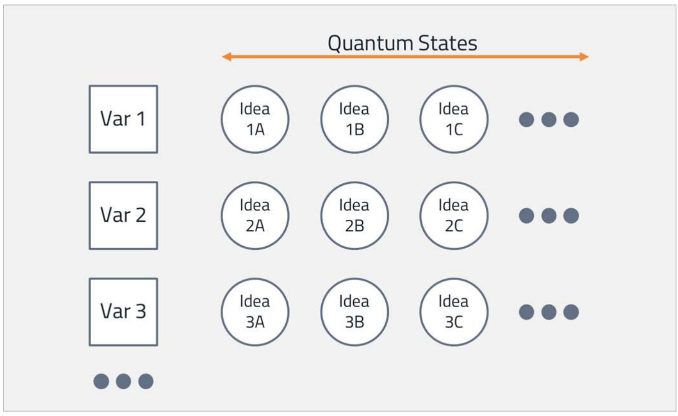
A TCC system must also be quick to train. The key factor in enabling a quick training time is a system's ability to train without annotated training data. Annotation of training data typically needs subject matter experts that are very expensive. Annotation is also a time intensive effort – some prominent implementations have taken years to train the data.

Finally, a TCC system must be configurable, at low cost, to a wide variety of situations in an enterprise. A key component of such configurability is the ability of tactical cognitive computing systems to be deployed over commoditized hardware in public cloud, in private cloud or on-premise.

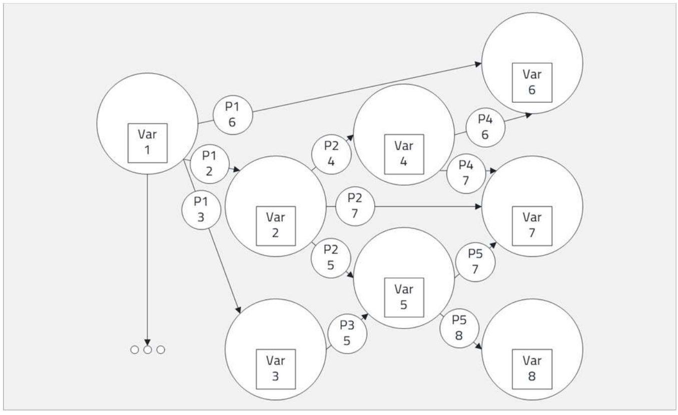
Coseer's implementation of TCC for natural language uses our work with Calibrated Quantum Mesh (CQM) and cognitive calibration, apart from various techniques in natural language processing, natural language understanding, and artificial intelligence.

B. *Calibrated Quantum Mesh*

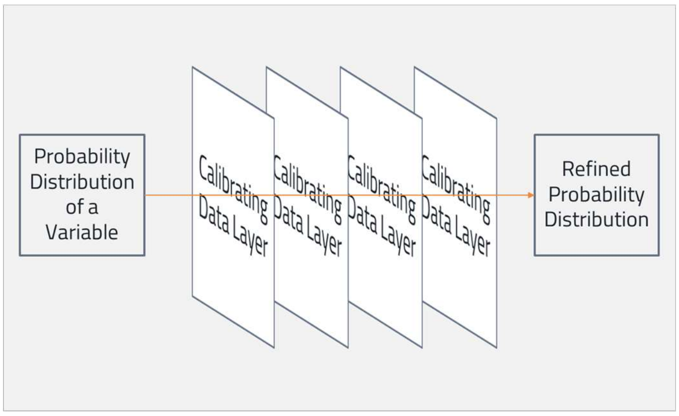
Calibrated Quantum Mesh (CQM) is a novel AI algorithm that is specifically built for understanding natural language as human beings do. It does not need annotated training data and reduces the need of unannotated data to a fraction.



I. Each variable is mapped to multiple Quantum States



II. Each data is connected to others in a Mesh.



III. External evidence helps the Mesh to converge.

Figure 1. Basic Tenets of Calibrated Quantum Mesh (CQM)

CQM works on three basic principles, as shown in Figure 1:

1. **Multiple meanings**: CQM recognizes that any symbol, word or text can have more than one meaning or quantum states with different probabilities. It considers all these possible states to find the most probable answer.

2. **Interconnectedness**: CQM recognizes that everything is correlated to each other and modifies each other's behavior. Specifically, each item can influence the probability

distribution across quantum states of all other items it is connected to. CQM considers such mesh of interconnections to reduce error.

3. **Calibration**: CQM sequentially adds all available information to help converge the mesh into a single meaning. The calibration process is fast, accurate and efficient in detecting any lacunas. The calibrations are implemented on training data, contextual data, reference data and other known facts about the problem. Sometimes these calibrating systems called Calibrating Data Layers are handled by an independent CQM module or another AI process.

When the training data is passed through CQM, it defines many of the mesh's interrelationships. Where applicable, data layer algorithms learn from such data. Often new relations and nodes are added to the mesh, making it smarter.

When a workflow is modeled by CQM, creation of any black boxes is avoided to the maximum extent. This ensures transparency and interpretability of the models.

We note that keywords are not important for CQM in processing natural language. Complex ideas are represented by different parts of the mesh with varying complexity. This enables the algorithm to handle fluid, multi-state and inter-connected knowledge – some inherent criteria of natural language.

The algorithm can also learn from non-direct corpuses. For example, while assisting a UK tax advisory, it was executed over HMRC.com, Law.com, Investopedia and a proprietary glossary.

The most important advantage of CQM is that it does not need annotated training data. As a result, training a CQM model is very fast and cost effective. It also allows iterations over the training process leading to highly accurate results. This capability qualifies CQM based systems to be part of TCC.

C. Cognitive Natural Language Search System

A cognitive search system can be applied to understand and interpret textual data in a natural way. [17] We used an algorithm based on CQM, which is also a TCC system, to develop a Natural Language Search system. We applied the Coseer system to assist users of AskCFPB with their questions.

The search system has two main steps: ingestion and search. In the ingestion step, documents are interpreted by the CQM and processed into relevant data structures. In this case it was the FAQs that were processed and stored in a database. Then a search module takes the query as input and searches the database for the relevant text or a snippet. The relevant text is then sent to the user as a possible answer to the query.

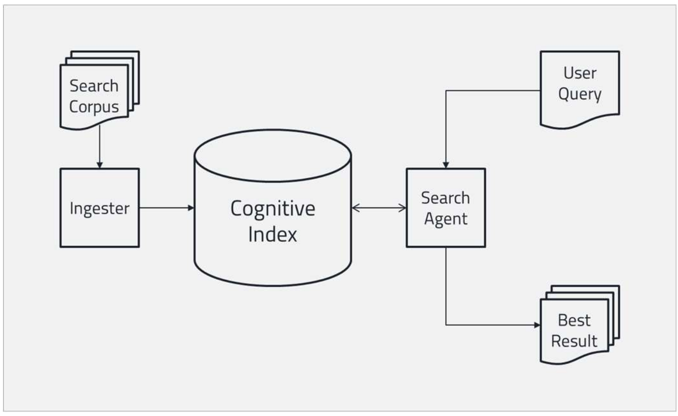


Figure 2: Overview of the cognitive search system.

Figure 2 illustrates the two main steps of the Coseer cognitive search system.

III. EVALUATION CRITERIA

The cognitive search system was evaluated in the following two ways:

1. Accuracy: This criterion measures how accurately the system answers the queries. It was calculated by dividing the number of queries correctly answered by the total number of queries. The search system was tested with 158 queries. For each query, the top three results returned by the system were evaluated by a human judge. The results were marked as relevant if any of the top three results satisfactorily answered the question.

2. Comparative performance: This evaluation criteria demonstrates how well the search system performs as compared to AskCFPB search. AskCFPB was selected for comparison because it is the most closely related search system. This system is powered by Bing Search Engine. For this evaluation criteria, 158 new queries were tested on both the search system. A human judge evaluated the top snippet in the following categories: COMPARABLE, COSEER_BETTER and ASKCFPB_BETTER, according to which result seemed more relevant to the query. While AskCFPB returns documents, not answers, we considered most relevant snippet identified by Bing Search Engine. We acknowledge that this is a very stringent evaluation criterion towards Coseer systems.

IV. RESULTS AND DISCUSSION

For the accuracy calculation, 130 out the of 158 queries were correctly answered by the Coseer cognitive search system, as evaluated by the human judge. This computes to 82.3% accuracy. This seems to be reasonable considering that the system was not trained for this subject matter.

For the comparative study, 158 new queries were considered. Figure 3 shows the results of the comparative study.

Out of the 158 queries, 26.6% showed comparable results. In 16.5% of the cases AskCFPB performed better than Coseer and in 57.0% of the cases, Coseer performed better than AskCFPB.

To get further insight about why one system works better than the other, we reported a couple of representative cases.

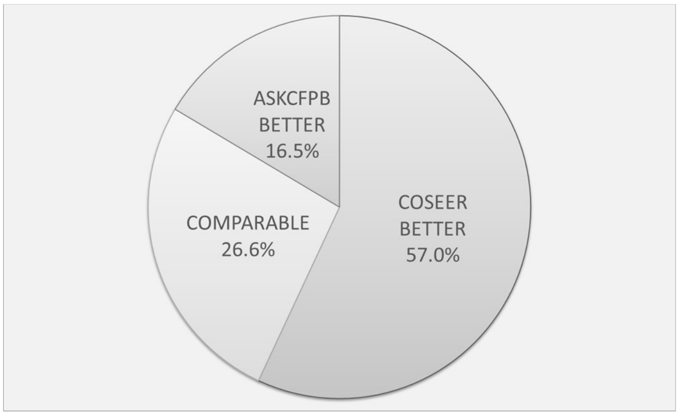


Figure 3: Results of comparative performance between AskCFPB and Coseer.

Table 1 shows two queries where Coseer performed better than AskCFPB.

There are several reasons behind the better performance of Coseer over AskCFPB. Unlike AskCFPB, Coseer considers the context of the query and the meaning of the query. It provides emphasis on the functional words like 'how long' instead of matching keywords. Similarly, Coseer considers all other possible meanings of the search query to execute its search. Special attention is given to the important phrases, abbreviations and colloquialisms.

Table 1. Cases where Coseer performed better than AskCFPB.

Query	Coseer answer	AskCFPB answer
How long do mortgages normally last?	How can I determine how long it will take me to pay off my mortgage loan?	What exactly happens when a mortgage lender checks my credit?
What type of rent information is on my credit report?	At least one of the big three consumer reporting agencies, Experian, uses rental payment and collection information in its credit reports.	What is a credit report? - Consumer Financial Protection ...

Table 2 reports a couple of cases where AskCFPB performed better than Coseer. The second query in Table 2 is of special interest. Although the question here is whether paying rent on time would strengthen credit history, the information about weakening of the credit history due to late payment is very relevant. Even though it appears to be diametrically the opposite answer, AskCFPB has correctly recognized such an answer as relevant. Coseer algorithm can be further improved by teaching it how to handle such cases.

Table 2. Cases where AskCFPB performed better than Coseer.

Query	Coseer answer	AskCFPB answer
What info does a credit report show?	If the investigation shows the company provided wrong information about you, or the information cannot be verified, the company must notify all the credit reporting companies to which it provided the wrong information...	A credit report is a statement that has information about your credit activity and current credit situation such as loan paying history and ...
Can I build my credit history by paying my rent on time?	You have a steady source of income and a good record of paying your bills on time. Lenders will look at your ability to repay the mortgage...	Could late rent payments or problems with a landlord be in my credit report?

V. CONCLUSION AND FUTURE WORK

Although Natural Language Search is an exciting and popular technology with ever increasing areas of applications, its ability to interact with people in a natural manner remains at an early stage. We applied a tactical cognitive computing system in conjugation with calibrated quantum mesh to develop a chatbot that helps customers with their questions. The search system demonstrated reasonable accuracy in assisting the users find the answers to their queries. Although there are several opportunities to improve, this comparative study demonstrates the usefulness of such an approach over typical key-word based natural language processing systems. It recommends cognitive computing as a key player in solving difficult problems that require humanlike thinking, ability to reason and extract meaning from information.

We plan to extend CQM for other basic cognitive processes like processing intonations in speech, translating ideas back into words and perhaps processing and expressing unarticulated thoughts and emotions in text.

Idea oriented chatbots can be the key for assimilating human and computing worlds. Coseer's solutions demonstrate that we are already capable of designing and training machines to process information like humans do, talk like humans do and provide business value like humans do.

Since the chatbots can run round the clock, at a fraction of the cost of a human resource and with high accuracy, it is perhaps not an overstatement to say that the future of the chatbot could be the future of all business.

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