Cognitive Database: A Step towards Endowing Relational Databases with Artificial Intelligence Capabilities

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ABSTRACT
We propose Cognitive Databases, an approach for transparently enabling Artificial Intelligence (AI) capabilities in relational databases. A novel aspect of our design is to first view the structured data source as meaningful unstructured text, and then use the text to build an unsupervised neural network model using a Natural Language Processing (NLP) technique called word embedding. This model captures the hidden inter-/intra-column relationships between database tokens of different types. For each database token, the model includes a vector that encodes contextual semantic relationships. We seamlessly integrate the word embedding model into existing SQL query infrastructure and use it to enable a new class of SQL-based analytics queries called cognitive intelligence (CI) queries. CI queries use the model vectors to enable complex queries such as semantic matching, inductive reasoning queries such as analogies, predictive queries using entities not present in a database, and, more generally, using knowledge from external sources. We demonstrate unique capabilities of Cognitive Databases using an Apache Spark based prototype to execute inductive reasoning CI queries over a multi-modal database containing text and images. We believe our first-of-a-kind system exemplifies using AI functionality to endow relational databases with capabilities that were previously very hard to realize in practice.

1. INTRODUCTION
Artificial Intelligence: Systems that perform actions that, if performed by humans, would be considered intelligent – Marvin Minsky

Wikipedia defines cognition as the mental action or process of acquiring knowledge and understanding through thought.

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experience, and the senses. In broad terms, cognition refers to the process of building knowledge capabilities using innate resources (i.e., intelligence), enriching it with external inputs such as experiences or interactions, and applying the knowledge to solve problems which feeds back towards knowledge building. While these definitions are more relevant to animate objects, they can be also applicable to scenarios in which inanimate entities simulate cognitive processes.

We focus on a particular cognitive process of reading comprehension of text via contexts and apply it to relational databases. In the relational model, some relationships between database values and entities are defined at the schema level: data types, keys, and functional (and other) dependencies. Relationships at the instance level (i.e., actual data tables) are left to be explored by queries. In a strong sense, the actual semantics of the data mostly lies in users’ minds and is expressed via queries. We take a significant diversion from this point of view. We postulate that there is significant latent knowledge in a database instance irrespective of querying. To capture this latent knowledge we propose to use Artificial Intelligence (AI) techniques that take advantage of contexts.

Specifically, in the relational database model, the main sources of latent information include the structure of database (e.g., column names in a relation) as well as the types of associated data values that include unstructured natural language text, strings, numerical values, images, SQL Dates etc. Together, these factors lead to inter- and intra-column semantic relationships. Current systems have limited support to exploit this information, namely via SQL and extensions such as text extenders [14] or RDF-based ontologies [38]. However, SQL queries rely mainly on value-based predicates to detect patterns. In addition, the relational data model ignores many inter- or intra-column relationships. Thus, traditional SQL queries lack a holistic view of the underlying relations and thus are unable to extract and exploit semantic relationships that are collectively generated by the various entities in a database relation.

A few examples may serve to clarify what we mean by latent knowledge. The first example considers a Human Resources (HR) database. This database contains relations with information about employees, their work history, pay grade, addresses, family members and more. Lately there have been some issues with an employee, John Dolittle. As a HR professional, you are interested in names of employees who know John well. Sure, you can get on the phone (or any
other media) and start making calls, collecting information until you have a few names of people with whom you would like to consult. Much of the information you will obtain is already hidden in the legacy database, but is diffused and hard to get at. This may include people who worked with John, managed him, complimented him, complained about him, provided technical services to him, were members of a small team with him and so on. Wouldn’t it be nice if you could write a SQL query that would use this hidden knowledge and essentially ask provide the names of the 10 employees most related to John Dolittle.

In the previous example, we relied on the content of the database in isolation. The next example involves entities external to the database. Suppose you have database of active vacations, featuring diving, hiking, skiing, desert driving and more. You are a bit worried as to which vacation package is the most dangerous one. Naturally, the official descriptions in the database will not always provide the information. It is likely that the words accident, danger, wounded, and death will not even be present in the database. These words are present in other data sources, from Wikipedia to news articles. Suppose you have access to such external sources. Wouldn’t it be nice if you could utilize these external sources and pose a SQL query expressing which are the most dangerous vacation packages. In this example, as well as the previous ones, you may want also to have a degree of certainty associated with each potential answer.

It is worth pointing out what distinguishes the level of intelligence we are looking for from known extensions to relational systems. In current systems one needs to pose a query based on some knowledge of the relational schema. The query may be assisted by text-aware features such as DB2 Text Extender [14], WordNet or using RDF-based ontologies [38]. These may be used to identify synonyms and related terms and relax the query by allowing it to explore more possibilities than those explicitly specified by the user [11]. Of course, such relaxation may result in obtaining a larger result set. But, all these useful features assume that the user knows how to specify a backbone query. The example problems we listed above are such that formulating an effective SQL query is a daunting task. In fact, these examples resemble research projects rather than standard queries. One can also allow the user to specify the query in natural language [37], but this pushes the problem of expressing a query to an automated tool; again, it is unclear how a tool will approach these problem if the tool’s writer does not have a ready recipe. This highlights the need of a new set of tools to enable far richer querying.

In this paper, we explore the potential of using Natural Language Processing (NLP) approaches to endow databases with query expression capabilities that were very hard, or perhaps impossible, to realize in practice, and at a reasonable cost in terms of storage overhead as well as processing time. The unique aspect of our proposal is to first represent the data and optionally, schema, of a (structured) relational database as an unstructured text document and then use a NLP technique, Vector Space Models (VSM) [55], to extract latent semantic relationships via associations in the generated text. The trained VSM model represents the semantic meaning of the words as vectors and enables operations on these vectors to mimic cognitive operations on natural language words. As these words represent relational entities and values, the VSM model, in fact, captures intra-/inter-column relationships in the relational database. We then integrate the VSM model into an existing standard SQL query processing system and expose the novel vector-based cognitive operations via a new class of SQL analytics queries, called Cognitive Intelligence (CI) queries [5]. We believe this is one of the first examples of AI transparently augmenting a relational database system. Clearly, this is only one of the many possible ways of integrating AI capabilities in database systems, e.g., for enhancing their querying capabilities or improving their operational capabilities [50, 59, 37]. While our current focus is on enhancing relational databases, we believe this approach can be applied to other database domains such as XML/RDF or JSON databases, document databases, graph databases, and key-value stores.

We are currently developing an Apache Spark-based prototype to implement our vision of an AI-enhanced cognitive relational database. The rest of the paper provides more details on the design and implementation of such a system. In Section 2, we introduce the vector space modeling process and detail the execution flow of the system we envisage. In Section 3, we provide specifics of the data preparation and building a specialized vector space model. In Section 4 we discuss three significant classes of CI queries: Similarity Queries, Inductive Reasoning Queries and Cognitive OLAP Queries; we also present cognitive extensions to the Relational Data Model. We also describe the design of Cognitive User Defined Functions (UDFs). Section 5 describes a practical scenario which demonstrates unique aspects of a cognitive database system: ability to invoke inductive reasoning (e.g., analogies, semantic clustering, etc.) queries over multi-modal data (e.g., images and text). We also discuss CI query performance issues, with focus on an important building block: Nearest-Neighbor Computations. Related work is discussed in Section 6 and we conclude by outlining extensions, future work, and success criteria in Section 7.

2. DESIGNING A COGNITIVE DATABASE

Our goal is to build a cognitive relational database system that not only extracts latent semantic information, but can also enrich it by using external input (e.g., external knowledge bases, new data being inserted, or types of invoked queries) and use it transparently to enhance its query capabilities. To achieve these goals, we rely on the VSM approach that infers word meanings using the distributional hypothesis, which states that words in a neighborhood (or context) contribute to each other’s meanings [21, 26]. Specifically, we use a predictive implementation of the VSM approach, commonly referred to as word embedding, which assumes a probabilistic language model to capture relationships between neighborhood words [8]. The word embedding approach fixes a d-dimensional vector space and associates a vector of continuous-valued real numbers to a word to encode the meaning of that word. Thus, for a given text corpus, the meaning of a word reflects collective contributions of neighborhood words for different appearances of the word in the corpus. Two words are closely related or have similar meaning if they appear often within close proximity of the same, or similar meaning, words. If two words have similar meaning, their meaning vectors point in very similar directions, i.e., the cosine similarity between their vectors is high (vector similarity is measured as a cosine of the angle
between two vectors and can vary from 1.0 to -1.0). One surprising application of word-embedding vectors is their usage in solving inductive reasoning problems such as computing analogies by using vector algebra calculations.

Over a past few years, a number of methods have been developed to implement the word embedding. Recently, an unsupervised neural network based approach, Word2Vec, has gained popularity due to its performance and ability to capture syntactic as well semantic properties of words. We use Word2Vec as it is easy to adapt, can be trained incrementally, and can be used for building models from both structured and unstructured data sources (alternatively, we could use approaches such as GloVe [51]).

In the database context, vectors may be produced by either learning on text transformed and extracted from the database itself and/or using external text sources. For learning from a database, a natural way of generating vectors is to apply the word embedding method to a string of tokens generated from the database: each row (tuple) would correspond to a sentence and a relation would correspond to a document. Thus, vectors enable a dual view of the data: relational and meaningful text. To illustrate this process, consider Figures 1 and 2 that present a simple customer sales table. Figure 1 shows an English sentence-like representation of the fourth row in the table (note that the numeric value 25.00 is represented by the string cluster_10). We discuss the reasons in the next section.). Using the scope of the generated sentence as the context, the word embedding approach inverts latent semantic information in terms of token associations and co-occurrences and encode it in vectors. Thus, the vectors capture first inter- and intra-column relationships within a row (sentence) and then aggregate these relationships across the relation (document) to compute the collective semantic relationships. At the end of training, each unique token in the database would be associated with a d-dimensional meaning vector, which can be then used to query the source database. As a simple example, the relational entity custD is semantically similar to custB due to many common semantic contributors (e.g., Merchant_B, Stationery, and Crayons). Equivalently, custA is similar to custC due to similar reasons.

![Figure 1: Example of customer analytics](image)

We may use a relational view of a table, rather than the original table, to generate text representing the database content. This may be useful for a supporting a particular class of applications. Consider a scenario in which a view of the table is defined (Figure 2), the view only projects data from the bold columns (Cust, Date, Address and Amount). In this case, the generated sentence-like representation would be different than the first case. Hence, it will generate a different word embedding model.

![Figure 2: Example of customer analytics with a different relational view](image)

This examples illustrates a key design feature of our cognitive database: the neighborhood context used for building the word embedding model is determined by the relational view being used. Hence, the inferred semantic meaning of the relational entities reflect the collective relationships defined by the associated relational view.

![Figure 3: End-to-end execution flow of a cognitive relational database](image)

The cognitive relational database has been designed as an extension to the underlying relational database, and thus supports all existing relational features. The cognitive relational database supports a new class of business intelligence (BI) queries called Cognitive Intelligence (CI) queries. The CI queries extract information from a relational database based, in part, on the contextual semantic relationships among database entities, encoded as meaning vectors. Figure 3 presents key phases in the end-to-end execution flow of a cognitive relational database system. The first, optional, phase involves (1) Generating token sequences from the database tables (textification), and then applying a word embedding model training method on the unstructured text corpus created from these token sequences. Following model training, the resultant vectors are stored in a relational system table (phase 2). At runtime, the SQL query execution engine uses various user-defined functions (UDFs) that fetch the trained vectors from the system table as needed and answer CI queries (phase 3). The CI queries take relations as input and return a relation as output. CI queries augment the capabilities of the traditional relational BI queries and can be used in conjunction with existing SQL operators (e.g., OLAP [22]).

3. BUILDING THE SEMANTIC MODEL

The key to artificial intelligence has always been the representation. —Jeff Hawkins

In this section, we discuss how we train a word embedding model using data from a relational database. Our training
approach is characterized by two unique aspects: (1) Using unstructured text representation of the structured relational data as input to the training process (i.e. irrespective of the associated SQL types, all entries from a relational database are converted to text tokens representing them), and (2) Using the unsupervised word embedding technique to generate meaningful vectors from the input text corpus. Every unique token from the input corpus is associated with a meaning vector. We now elaborate on these two aspects.

3.1 Data Preparation

The data preparation stage takes a relational table with different SQL types as input and returns an unstructured but meaningful text corpus consisting of a set of sentences. This transformation allows us to generate a uniform semantic representation of different SQL types. This process of textification requires two stages: data pre-processing and text conversion (Figure 4).

\[ \text{Relational Data} \rightarrow \text{Preprocessing} \rightarrow \text{Meaningful Text} \]

\[ \text{Word Embedding} \rightarrow \text{Unsupervised Model} \rightarrow \text{Trained Model} \]

Figure 4: Multiple stages in creating the word embedding model

The textification phase processes each relational row separately and for each row, converts data of different SQL data types to text. In some scenarios, one may want to build a model that also captures relational column names. For such cases, the pre-processing stage first processes the column names before processing the corresponding data.

For SQL variables of VARCHAR type, pre-processing involves one or more of the following actions: (1) prepend the column attribute string to a SQL variable, (2) creating a single concept token from a group of VARCHAR tokens, e.g., JPMorgan Chase is represented as JPMorgan_Chase, (3) creating a single token for semantically similar sequences of VARCHAR tokens, e.g., two sequences of tokens, bank of america and BANK OF AMERICA, can be represented by a single compound token BANK_OF_AMERICA, and (4) Using an external mapping or domain-specific ontologies to create a common representative token for a group of different input tokens. This approach is useful for enabling transfer learning via reusing the same training model for a group of related tokens. After pre-processing, all input text tokens have uniform representations.

In addition to text tokens, our current implementation supports numeric values and images (we assume that the database being queried contains a VARCHAR column storing links to the images). These techniques can be applied to other SQL datatypes such as SQL Date as well. For numeric values, we use three different approaches to generate equivalent text representations: (1) creating a string version of the numerical value, e.g., value 100.0 for the column name price can be represented by either PRICE_100.0 or ‘100.0’, (2) User-managed categorization: a user can specify rules to define ranges for the numeric values and use them to generate string tokens for the numeric values. For example, consider values for a column name, Cocoa Content. The value 80% can be replaced by the string token choc_dark, while the value 35%, can be replaced by the string token choc_med, etc., and (3) user-directed clustering: an user can choose values of one or more numerical columns and cluster them using traditional clustering algorithms such as K-Means. Each numeric value is then replaced by a string representing the cluster in which that value lies (e.g., cluster_10 for value 25 in Figure 1).

For image data, we use approaches similar to ones used for numerical values. The first approach represents an image by its string token, e.g., a string representing the image path or a unique identifier. The second approach uses pre-existing classifiers to cluster images into groups and then uses the cluster information as the string representation of the image. For example, one can use a domain-specific deep neural network (DNN) based classifier to cluster input images into classes [31] and then use the corresponding class information to create the string identifiers for the images. The final approach applies of-the-shelf image to tag generators, e.g., IBM Watson Visual Recognition System (VRS) [30], to extract image features and uses them as string identifiers for an image. For example, a Lion image can be represented by the following string features, Animal, Mammal, Carnivore, BigCat, Yellow, etc.

Once text, numeric values and images are replaced by their text representations, a relational table can be viewed as unstructured meaningful text corpus to be used for building an word embedding model. For Null values of these types, we replace them by the string column_name_Null. The methods outlined here can be applied to other data types such as SQL Date and spatial data types such as latitude and longitude.

3.2 Model Training

We use an unsupervised approach, based on the Word2Vec (W2V) implementation [42], to build the word embedding model from the relational database data. Our training approach operates on the unstructured text corpus, organized as a collection of English-like sentences, separated by stop words (e.g., newline). There is no need of labelling the training data as we use unsupervised training. Another advantage of unsupervised training is that users do not need to do any feature engineering [20], features of the training set are extracted automatically by the training process.

During model training, the classical W2V implementation uses a simplified 3-layer shallow neural network that views the input text corpus as a sequence of sentences. For each word in a sentence, the W2V code defines a neighborhood window to compute the contributions of nearby words. Unlike deep learning based classifiers, the output of W2V is a set of vectors of real values of dimension d, one for each unique token in the training set (the vector space dimension d is independent of the token vocabulary size). In our scenario, a text token in a training set can represent either text, numeric, or image data. Thus, the model builds a joint latent representation that integrates information across different modalities using untyped uniform feature (or meaning) vectors.

Our training implementation builds on the classical W2V implementation, but it varies from the classical approach in
a number of ways (Figure 4):

- A sentence generated from a relational row is generally not in any natural language such as English. Therefore, W2V’s assumption that the influence of any word on a nearby word decreases as the word distances increases, is not applicable. In our implementation, every token in the training set has the same influence on the nearby tokens; i.e. we view the generated sentence as a bag of words, rather than an ordered sequence.

- Another consequence is that unlike an English sentence, the last word is equally related to the first word as to its other neighbors. To enable such relationships, we use a circular neighborhood window that wraps around a sentence (i.e. for the last word, the first word can be viewed as its immediate neighbor).

- For relational data, we provide special consideration to primary keys. First, the classical W2V discards less frequent words from computations. In our implementation, every token, irrespective of its frequency, is assigned a vector. Second, irrespective of the distance, a primary key is considered a neighbor of every other word in a sentence and included in the neighborhood window for each word. Also, the neighborhood extends via foreign key occurrences of a key value to the row in which that value is key.

- In some cases, one may want to build a model in which values of particular columns are given higher weightage for their contributions towards meanings of neighborhood words. Our implementation enables users to specify different weights (or attention [3]) for different columns during model training (in this scenario, one needs to use a training set in which column names are embedded).

- Finally, our implementation is designed to enable incremental training, i.e. the training system takes as input a pre-trained model and a new set of generated sentences, and returns an updated model. This capability is critical as a database can be updated regularly and one can not rebuild the model from scratch every time. The pre-trained model can be built from the database being queried, or from an external source. Such sources may be publicly available general sources (e.g., Wikipedia), text from a specific domain (e.g., from the FDA regarding medical drugs), text textified from other databases or text formed from a different subset of tables of the same database. The use of pre-trained models is an example of transfer learning, where a model trained on an external knowledge base can be used either for querying purposes or as a basis of a new model [20].

In practice, enterprise database systems, as well as data warehouses, are built using many inter-related database tables. Forming a training corpus from multiple tables is non-trivial. There are numerous options, including:

- Build separate models (i.e. a set of word vectors), each based on an individual, informative, table.

Figure 5: Text view of two tables joined using primary and foreign keys

- Build models each based on linked tables where, usually, the linking is based on foreign keys appearing in say table A pointing to tuples into another, say table B. When a foreign key is present, during tokenization of table A, we can follow the foreign key to a row in table B. We can then tokenize fields of interest in the row of table B and insert the resulting sequences into the sequence generated for table A. Figure 5 presents another example of a database table, address, and a resulting token sequence that utilizes a relationship between the empl table and the address table; namely the address table provides the addresses for the employees of database table empl. Technically, the resulting token sequence is based on foreign key 119 in the address column of the table emp which provides a value for key column id of the address table. The straight forward way to tokenize with foreign keys is to insert the subsequence generated out of the B row immediately after the one generated for the A row as depicted in Figure 5. Another possibility is to intermix the subsequence from the B row within the A row sequence following the tokenization of the foreign keys values (again, other options may apply).

- A collection of tables may be identified and textified into a collection of texts. These texts may be concatenated to form a single text which may be used in training. The tables in this collection should form a coherent informative subset of the database.

- In all the options above, the training text may be augmented with text from external sources.

4. BUILDING A COGNITIVE DATABASE SYSTEM

Cognitive intelligence (CI) queries are standard SQL queries and can be implemented using the existing SQL query execution infrastructure. The distinguishing aspect of cognitive intelligence queries, contextual semantic comparison between relational variables, is implemented using user-defined functions (UDFs). These UDFs, termed cognitize UDFs, take typed relational values as input and compute semantic relationships between them using uniformly untyped meaning vectors. This enables the relational database system to seamlessly analyze data of different types (e.g., text, numeric values, and images) using the same SQL CI query.

Our current implementation is built on the Apache Spark 2.2.0 infrastructure. Our system follows the cognitive database
execution flow as presented in Figure 3. The system first initializes in-memory Spark Dataframes from external data sources (e.g., relational database or CSV files), loads the associated word embedding model into another Spark Dataframe (which can be created offline from either the database being queried or external knowledge bases such as Wikipedia), and then invokes CI queries using Spark SQL. The SQL queries invoke Scala-based cognitive UDFs to enable computations on the meaning vectors (we also provide a Python based implementation).

4.1 Design of Cognitive UDFs

A cognitive UDF takes as input either relational query variables or constant tokens, and returns a numeric similarity value that measures the semantic relationships between the input parameters. A user can then control the result of the CI query by using a numerical bound for similarity result value as a predicate for selecting eligible rows. A user can also use SQL ordering clauses, DESC or ASC, to order results based on the similarity value that captures the semantic closeness between the relational variables: higher is the similarity value, closer are these two relational variables. The UDFs perform three key tasks: (1) processing input relational variables to generate tokens used for training. This involves potentially repeating the steps executed during the data preparation stage, such as creating compound tokens. For numeric values, one can use the centroid information to identify the corresponding clusters. For images, the UDF uses the image name to obtain corresponding text tokens, (2) Once the training tokens are extracted, the UDF uses them to fetch corresponding meaning vectors, and (3) Finally, the UDF uses the fetched vectors to execute similarity computations to generate the final semantic relationship score.

The basic cognitive UDF operates on a pair of sets (or sequences) of tokens associated with the input relational parameters (note: value of a relational parameter can be a set, e.g., [Bananas, Apples], see Figure 1). The core computational operation of a cognitive UDF is to calculate similarity between a pair of tokens by computing the cosine distance between the corresponding vectors. For two vectors $v_1$ and $v_2$, the cosine distance is computed as $\cos(v_1, v_2) = \frac{v_1 \cdot v_2}{\|v_1\|\|v_2\|}$. The cosine distance value varies from 1.0 (very similar) to -1.0 (very dissimilar). For sets and sequences, the individual pair-wise distances contribute equally to the final result.

4.2 Cognitive Intelligence Queries

The basic UDF and its extensions are invoked by the SQL CI queries to enable semantic operations on relational variables. Each CI query uses the UDFs to execute nearest neighbor computations using the vectors from the current word-embedding model. Thus, CI queries provide approximate answers that reflect a given model. The CI queries can be broadly classified into four categories as follows:

(1) Similarity/Dissimilarity Queries: The basic UDF that compares two sets of relational variables can be integrated into an existing SQL query to form a similarity CI query. Figure 6 illustrates a SQL CI query that identifies similar customers by comparing their purchases. Assume that sales is a table that contains all customer transactions for a credit card company and whose sales.Items column contains all items purchased in a transaction (Figure 1). The current query uses a UDF, similarityUDF(), that computes similarity match between two sets of vectors, that correspond to the items purchased by the corresponding customers. Unlike the food item scenario, the purchased item list can be viewed as an unordered bag of items; and individual pair-wise distances contribute equally to the final result. The query shown in Figure 6 uses the similarity score to select rows with related customers and returns an ordered set of similar customer IDs sorted in descending order of their similarity score. This query can be easily tweaked to identify dissimilar customers based on their purchases. The modified CI query will first choose rows whose purchases have lower similarity (e.g., $< 0.3$) and if the results are ordered in an ascending form using the SQL ASC keyword, returns customers that are highly dissimilar to a given customer (i.e., purchasing very different items). If the results are ordered in the descending order using the SQL DESC keyword, the CI query will return customers that are somewhat dissimilar to a given customer.

SELECT X.custID, Y.custID, similarityUDF(X.Items, Y.Items) AS similarity
FROM sales X, sales Y
WHERE similarityUDF(X.Items, Y.Items) > 0.5
ORDER BY similarity DESC

Figure 6: Example of an CI similarity query: find similar customers based on their purchased items

A modified version of the query (not shown) can identify similar customers based on their overall purchasing pattern as evidenced in a number of rows. The word embedding model creates a vector for each customer name that captures the overall purchases made by that customer. Then, the customers with similar purchase patterns would have vectors that are close using the cosine distance metric. The pattern observed in this query can be applied to other domains as well, e.g., identifying patients that are taking similar drugs, but with different brand names, or identifying food items with similar ingredients, or recommending mutual funds with similar investment strategies. As we will see in the next section, the similarity query can be applied other data types, such as images.

SELECT X.custID, Y.custID, Y.Merchant, valueSimUDF(X.Amount, Y.Amount) AS similarity
FROM sales X, sales Y
WHERE X.custID='custA' AND valueSimUDF(X.Amount, Y.Amount) > 0.5 AND X.custID != Y.custID AND X.amount > 150.0 AND Y.amount < 100.0
ORDER BY similarity DESC

Figure 7: Example of an CI value similarity query: find similar transactions using purchased amount for comparison
SELECT X.custID, similarityUDF(X.Items, 'listeria') AS similarity
FROM sales X
WHERE similarityUDF(X.Items, 'listeria') > 0.3
ORDER BY similarity DESC
LIMIT 10

Figure 8: Example of a prediction query: find customers that have purchased items affected by a listeria recall

Figure 7 presents a CI query executing similarity operations using a numeric variable. For the sake of example, assume that no two transactions have the same amount value and each unique numerical value is associated with its own string token. In this scenario, one wants to identify transactions from the sales table (Figure 1): using similarity based on the purchase amount (in this case, 200.50 for customer custA). The UDF, valueSimUDF(), takes two numeric values as input parameters, and compares them using their overall context (which is captured in their meaning vectors), not their numerical values. The most similar amount to 200.50, would be 80.10 (for customer custC), as it shares the most context (e.g., category, address, merchant, and items). The least similar amount would be 60.80 as it has completely different context than amount 200.50. This example also illustrates how one can combine the value-based and semantic-based comparisons in the same SQL query.

The third use case provides an illustration of a prediction CI query which uses a model that is externally trained using an unstructured data source or another database (Figure 8). Consider a scenario of a recall of various fresh fruit types due to listeria recall. The model will create word embedding vectors for terms like Apples, Peaches, Plums, Nectarines,.. Based on their meaning vectors, the UDF, similarityUDF(), identifies those purchases that contain items affected by the recall, as defined by the model. For the sake of example, as-is follows, the similarityUDF() UDF is used to identify those purchases that contain items similar to listeria, such as Apples. This example demonstrates a very powerful ability of CI queries that enables users to query a database using a token not present in the database (e.g., listeria). This capability can be applied to different scenarios in which recent, updatable information, can be used to query historical data. For example, a model built using FDA recall notices could be used to identify those customers who have purchased medicines similar to the recalled medicines.

(2) Inductive Reasoning Queries: An unique feature of word-embedding vectors is their capability to answer inductive reasoning queries that enable an individual to reason from part to whole, or from particular to general [54][55]. Solutions to inductive reasoning queries exploit latent semantic structure in the trained model via algebraic operations on the corresponding vectors. We encapsulate these operations in UDFs to support following five types of inductive reasoning queries: analogies, semantic clustering, analogy sequences, clustered analogies, and odd-man-out [54].

SELECT X.custID, analogyUDF('Frozen Goods', 'custF', 'Fresh Produce', X.custID) AS similarity
FROM sales X
WHERE analogyUDF('Frozen Goods', 'C3423567', 'Fresh Produce', X.custID) > 0.5
ORDER BY similarity DESC

Figure 9: Example of an analogy query

- Analogies: Wikipedia defines analogy as a process of transferring information or meaning from one subject to another. A common way of expressing an analogy is to use relationship between a pair of entities, source_1 and target_1, to reason about a possible target entity, target_2, associated with another known source entity, source_2. An example of an analogy query is Lawyer: Client :: Doctor ::, whose answer is Patient. To solve an analogy problem of the form (X :: Y :: Q ::?), one needs to find a token W whose meaning vector, V_W, is closest to the ideal response vector V_R, where V_R = (V_Q + V_Y - V_X) [54]. Recently, several solutions have been proposed to solve this formulation of the analogy query [35, 39, 45]. We have implemented the 3COSMUL approach [35] which uses both the absolute distance and direction for identifying the vector V_W as

$$
\text{arg max}_{W \in C} \frac{\cos(V_W, V_Q)\cos(V_W, V_Y)}{\cos(V_W, V_X) + \epsilon}
$$

where $\epsilon = 0.001$ is used to avoid the denominator becoming 0. Also, 3COSMUL converts the cosine similarity value of c to $\frac{(c+1)}{2}$ to ensure that the value being maximized is non-negative.

Figure 9 illustrates a CI query that performs an analogy computation on the relational variables using the UDF analogyUDF(). This query aims to find a customer from the sales table (Figure 1), whose relationship to the category, Fresh Produce, is similar to what C3423567 has with the category, Frozen Goods (i.e. if C3423567 is the most prolific shopper of frozen goods, find other customers who are the most prolific shoppers of fresh produce). The analogyUDF() UDF fetches vectors for the input variables, and using the 3COSMUL approach, returns the analogy score between a vector corresponding to the input token and the computed response vector. Those rows, whose variables (e.g., custID) have analogy score greater than a specified bound (0.5), are selected, and returned in descending order of the score. Since analogy operation is implemented using untyped vectors, the analogyUDF() UDF can be used to capture relationships between variables of different types, e.g., images and text.

- Semantic Clustering: Given a set of input entities, {X, Y, Z, ...}, the semantic clustering process identifies a set of entities, {W, ...}, that share the most dominant trait with the input data. The semantic clustering operation has a wide set of applications, including customer segmentation, recommendation, etc. Figure 10 presents a CI query which uses a semantic clustering UDF, semclusterUDF(), to identify customers that...
SELECT X.custID, semclusterUDF('custX', 'custY', 'custZ', X.custID) AS similarity
FROM sales X
WHERE semclusterUDF('custX', 'custY', 'custZ', X.custID) > 0.5
ORDER BY similarity DESC

Figure 10: Example of a semantic clustering query

have the most common attributes with the input set of customers, e.g., custF, custM, and custR. For solving a semantic clustering query of the form, \((X, Y, Z :: ?)\), one needs to find a set of tokens \(S_w = \{W_1, W_2, ..., W_i\}\) whose meaning vectors \(V_w\) are most similar to the centroid of vectors \(V_X, V_Y, \) and \(V_Z\) (the centroid vectors capture the dominant features of the input entities).

- Analogy Sequences and Clustered Analogies: These two types of inductive reasoning queries, analogy sequences and clustered analogies, can be implemented by combining strategies for semantic clustering and analogies. The analogy sequence query takes as input a sequence of analogy pairs, with the same source entity and aims to identify a set of target entities that exhibit the same relationships with the source entity as the set of input target entities. To answer this query, one needs to first compute the centroid vector of the input target vectors and then use it to answer the following analogy problem: \(source : input\_centroid :: source ?\) using the 3COSMUL approach to return a set of target entities.

Unlike analogy sequences, the clustered analogy operation takes as input a set of analogy pairs, each with different \((source_i, target_i)\) entity pairs and aims to predict a set of \((source_o, target_o)\) pairs that shares the following relationships with the input sequence: the result set of source entities, \(source_o\), share the dominant trait with the input set of source entities, \(source_i\), and each resultant target entity, \(target_o\), is related to the corresponding source entity via the analogy relationship. Therefore, to solve clustered analogy queries, we first perform semantic clustering to compute the result source entities, \(source_o\), and then for each result source entity, we compute a set of target entities using the analogy sequence approach. Unlike the analogy sequences query, the result of the clustered analogy query is a set of sets: a set of source entities, each associated with a set of target entities.

- Odd-man-out\(^2\) As the name suggests, given a set of items, the odd-man-out query identifies an item that is semantically different from the remaining items\(^1\). The odd-man-out query can be viewed as a complementary query to semantic clustering. For example, given a set of animals, \{Hippopotamus, Giraffe, Elephant, and Lion\}, one answer can be Lion, as it is only carnivorous animal in the collection. However, if the word-embedding model of these animals captures their locations, Elephant may be the answer if it is not present in that location. Thus, the odd-man-out execution requires context-specific semantic clustering over the meaning vectors. Specifically, the clustering aims to partition the data into two clusters, one with only one member, and the other containing the remaining data. One obvious application of the odd-man-out CI query would anomaly detection, e.g., for identifying a fraudulent transaction for a customer.

(3) Cognitive OLAP Queries: Figure 11 presents a simple example of using semantic similarities in the context of a traditional SQL aggregation query. This CI query aims to extract the maximum sale amount for each product category in the sales table for each merchant that is similar to a specified merchant, Merchant\_Y. The result is collated using the values of the product category. As illustrated earlier, the UDF similarityUDF can also be used for identifying customers that are different than the specified merchant. The UDF can use either an externally trained or locally trained model. This query can be easily adapted to support other SQL aggregation functions such as \(\text{MAX}(\cdot), \text{MIN}(\cdot), \text{and AVG}(\cdot)\). This query can be further extended to support ROLLUP operations over the aggregated values\(^27\).

We are also exploring integration of cognitive capabilities into additional SQL operators, e.g., IN and BETWEEN. For example, one or both of the value ranges for the BETWEEN operator can be computed using a similarity CI query. For an IN query, the associated set of choices can be generated by a similarity or inductive reasoning queries. Another intriguing extension involves using contextual similarities to choose members of the schema dimension hierarchy for aggregation operations like ROLLUP or CUBE. For example, instead of aggregating over all quarters for all years, one can use only those quarters that are semantically similar to a specified quarter.

(4) Cognitive Extensions to the Relational Data Model: There are powerful extensions to SQL that are enabled by word vectors. For this we need the ability to refer to constituent tokens (extracted during textification) in columns of rows, in whole rows and in whole relations. The extension is via a declaration, in the FROM clause, of the form Token \(e_1\) that states that variable \(e_1\) refers to a token. To locate a token we use, in the WHERE clause, predicates of the form contains\((E, e_1)\) where \(E\) can be a column in a row (e.g., EMP\_Address), a whole row (e.g., EMP\_*) or a whole relation (e.g., EMP). With this extension we can easily express queries such as asking for an employee whose Address contains a token which is very close to a token in a row in the DEPT relation (Figure 12). Furthermore, we can also extend SQL with relational variables, say of the form $\text{SR}$ and column variables, say \(X\), whose names are not specified at query writing time; they are bound at runtime. We can then use these variables in queries, in conjunction with Token variables. This enables database querying without explicit schema knowledge which is useful for exploring a database. Interestingly, the

Figure 11: Example of a cognitive OLAP (aggregation) query

\[\text{SELECT X.category, MAX(X.Amount)}\]
FROM sales X
WHERE similarityUDF('Merchant\_Y', X.Merchant) > 0.5
GROUP BY X.category
notation $\mathbf{R}_{X}$ is basically syntactic sugar. A software translation tool can substitute for $\mathbf{R}_{X}$ an actual table name and an actual column. Then, perform the query for each such substitution and return the union of the results.

$$\cosineDistance(e_1, e_2) > 0.75$$

Figure 12: Example of an SQL query with entities

Lastly, one may wonder how numeric bounds on UDFs (e.g., $\cosineDistance(e_1, e_2) > 0.75$ in Figure 12) are determined. The short answer is that these bounds are application dependent, much like hyperparameters in machine learning. One learns these by exploring the underlying database and running experiments. In the future, one can envision a tool that can guide users to select an appropriate numeric bound for a particular CI query.

5. COGNITIVE QUERIES IN PRACTICE

We now illustrate some unique capabilities of our cognitive database system by discussing a scenario in which CI queries are used to gain novel insights from a multi-modal relational database.

In this scenario, we consider a database of national parks across multiple countries, with links to images of animals in the associated national parks (Figure 13(A)). We use images from the open source Image database, ImageNet [16], to populate our database. We use this database to present results from inductive reasoning CI queries using our Spark 2.2.0 based prototype on an Intel Xeon E5-2680 system. Our prototype is implemented in Scala and supports queries written in either Scala or Python using Spark SQL, Spark Dataframes, or Python pandas SQLite interfaces. Although the database under evaluation is fairly simple, its architecture is similar to many other real life databases, e.g., a multi-modal patient database with text fields describing patient characteristics and image fields referring to associated images (e.g., radiology or FMRI images), or an insurance claims database with text fields containing the claim information and image fields storing supporting pictures (e.g., car collision photos).

Figure 13(A) presents the original relational table as created by an user. It contains only text fields that list paths to the images and provide additional information on every image. This table, other than the image path, does not provide any details on the referred images. To create a shared word embedding model from the text and images, we employ the automatic tag generator approach outlined in Section 3.1.

Figure 13 presents the workflow of extracting image features from the referred images. Each image in the database (e.g., a Lion) is first uploaded to the IBM Watson Visual Recognition System (VRS) [30] for classification and text description. The Watson system’s JSON response is then parsed, and a set of text attributes for the input image is extracted. These attributes form the features of the images and are added to the original table to create a training version of the table (Figure 13(B)). This training table can be used to build the text corpus for training the word embedding model.

Figure 14 presents the workflow of extracting image features (Figure 14(C)) to build the text corpus for training the word embedding model. Each sentence in the text corpus includes both original non-image (e.g., Corbett) and extracted image features (e.g., Tiger, or Carnivorous). In the resulting multi-modal word embedding model, the non-image features will contribute to the meaning of image features and vice versa, and all meaning vectors will be uniformly represented using vectors of dimension $d = 200$.

Once the meaning vectors are computed they can be used either hidden or exposed to the user. The training table is then converted to the textual representation (Figure 14(C)) to build the word corpus. Each sentence in the text corpus includes both original non-image (e.g., Corbett) and extracted image features (e.g., Tiger, or Carnivorous). In the resulting multi-modal word embedding model, the non-image features will contribute to the meaning of image features and vice versa, and all meaning vectors will be uniformly represented using vectors of dimension $d = 200$.

Due to space limitations, we focus only on certain types of queries.

**Figure 13:** Steps in training a multi-modal database with text and image fields

**Figure 14:** Illustration of workflow to generate a Text Attribute Database of images using the IBM Watson Visual Recognition Service (VRS) using a sample image from ImageNet dataset

Once the meaning vectors are computed they can be used to evaluate semantic relationships between values in the original relational table. For example, if one were to compare National Parks, Serengeti and Sunderbans would be the most similar as they both share multiple image features. It should be noted that one cannot get this insight by using standard SQL queries as the original table does not have any image information. Further, as many values in the training database are syntactically different (e.g., Crocodile and Indian Gharial), existing SQL systems will fail to extract any semantic similarities.

The first two examples of SQL CI queries over multi-modal data assume that the users have access to the training database (Figure 13(B)). Figure 15 illustrates an analogy
query over images, while Figure 16 illustrates an analogy sequence query. In both cases, the CI queries are formulated using UDFs, analogyQuery() and analogySequence(), that take values from the training database as input. In case of the analogy query, the goal is to find all images whose classD feature (i.e. extracted name) has the same relationship to its classC feature (i.e. class aquatic_vertebrate) as the specified relationship, reptile: monitor_lizard. For each row in the table, the UDF first fetches meaning vectors for the input parameters and uses the 3COSMUL approach to find a relational value whose vector maximizes the analogy similarity score as defined in Equation 1. The SQL query returns the corresponding images, whose similarity score is higher than 0.5 and reports them in a descending order of similarity score. Figure 15 presents an output fragment of the CI query and the corresponding images of spiny_finned_fish.

The analogy sequence query (Figure 16) uses a UDF that operates on a sequence of analogy pairs that share the source entity (e.g., mammal), but has different target entities, (e.g., jackal and mongoose). The UDF converts the analogy sequence problem into a traditional analogy problem by first computing the average vector of the target entities and then using it in the 3COSMUL approach. Figure 16 presents the SQL CI query, the analogy sequence UDF, and its output (images of grey fox).

Figure 15: Analogy queries over images

Figure 16: Analogy sequence queries over images

The next example (Figure 17) illustrates execution of a semantic clustering query on the original multi-modal database table. The goal of this query is to identify all images that are similar to every image in the set of user chosen images. Such images share one or more features with the input set of images. For this query, we select images of a lion, a vulture, and a shark as the input set and use the combinedAvgSim() UDF to identify images that are similar to all these three images. Although the input images display animals from three different classes, they share one common feature: all three animals are carnivorous. The UDF computes the average vector from the three input images and then selects those images whose vectors are similar to the computed average vector with similarity score higher than 0.75. Figure 17 shows the top three image results: andean condor, gluton wolverine, and tyra. Although these animals are from different classes, they are all carnivores, a feature that is shared with the animals from the input set.

Figure 17: Semantic clustering of images
5.1 Optimizing Cognitive Intelligence Queries

Cognitive Intelligence queries are standard SQL analytics queries which invoke UDFs to enable contextual semantic operations between relational tables. Irrespective of the kind of CI Query, core UDF computation involves computing pair-wise similarities between vectors, which can be then used to identify nearest or furtthest neighbors of a vector. In the worst case, a CI query can invoke a UDF for every row combination being evaluated and the UDF, in turn, can operate on a large number of vectors. Since in practice, the number of row combinations can very high, it is critical to optimize the performance of distance computations in the nearest-neighbor calculations for CI queries.

In a d dimensional vector space, pair-wise distance between vectors \( v_1 \) and \( v_2 \) is calculated by computing the cosine similarity, \( \cos(v_1, v_2) = \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|} \). As we use normalized forms of vectors (i.e., \( \|v\| = 1 \)), the pair-wise distance calculation gets simplified to a vector dotproduct, \( v_1 \cdot v_2 \). In general, there are four basic ways of optimizing distance computations:

- **Increasing computation granularity**: In cases where one needs to compute the distance of a vector from many vectors, many individual dotproduct operations can be converted into a single matrix-vector multiplication operation. This can be generalized to a matrix-matrix multiplication operation to enable distance computations between two sets of vectors.

- **Reducing redundant computations**: For a given vector, we can first identify a candidate set of vectors that are spatially closer to it in the d dimensional vector space using either locality sensitive hashing (LSH) or clustering via the Spherical K-Means algorithm. We can then invoke distance calculations on the candidate set to compute precise distances. In the LSH approach, the d dimension vector locations are mapped to bit-vector *signatures* of length d via projecting them on random planes. For a given vector, spatially closer vectors can be identified by choosing those with small hamming distance (1 or 2) between their corresponding signatures. In the K-Means approach, one can use the centroid information to identify a candidate set of spatially close vectors. Both approaches can also be accelerated using either SIMD functions or GPUs.

- **Using relational query optimization approaches**: One can also reduce redundant computations by using relational view that pre-selects rows from a table based on certain criteria. In addition, once the candidate set of SQL variables is known, the SQL query engine can pre-compute the pair-wise distances and use the cached results during execution of UDFs later.

- **Using hardware acceleration and parallelization**: The core nearest-neighbor distance computations, namely, dotproduct, matrix-vector, and matrix-matrix computations can be accelerated via hardware accelerators such as on-chip SIMD or using GPUs. Most numerical libraries such as MKL, ESSL, or OpenBLAS provide hardware accelerated matrix computation kernels. Further, the nearest neighbor computations can be also parallelized either using CPU-based multithreading (e.g., using pthreads) or distributing it over a cluster of machines using a distributed infrastructure such as the Apache Spark.

Optimizations of the cognitive intelligence queries is an open problem and is the current focus of our activities.

6. RELATED WORK

**Language Embedding**: Over the past few years, a number of methods have been introduced for obtaining a vector representation of words in a language [5], called *language embedding*. The methods range from *brute force* learning by various types of neural networks (NNs) [6] to log-linear classifiers [49] and to various matrix formulations, such as matrix factorization techniques [56]. Lately, Word2Vec [42, 44, 45, 35] has gained prominence as the vectors it produces appear to capture syntactic and semantic properties of words. The exact mechanism employed by Word2Vec and suggestions for alternatives are the subject of much research [46, 47, 19, 35]. Although Word2Vec has gained much prominence it is one of many possible methods for generating word representing vectors. For example, GloVe [31] also builds word embeddings by a function optimization approach over the word co-occurrence matrix. Vectors may be associated with larger bodies of text such as paragraphs and
even documents. Applications to the paragraph and document embedding appear in [34, 15]. Recent work has also been exploring applying word embeddings to capture image semantics [57].

**Applications of Word Embedding:** The word embedding model is being used for a wide variety of applications beyond NLP. Wu et al [64] provide a general neural framework for building vector embeddings of entities of different types into a vectorial embedding space. The common representation can be then used for different tasks such as text classification, link prediction, document recommendation, etc. The YouTube recommendation system uses embedding approaches to capture user behavior [13]. Similar embedding-based approaches have been used for recommending news articles [48], for discovering topics [65], or for personalized fashion shopping [47, 2]. Hope et. al. have proposed using word embedding for supporting analogy queries over knowledge bases such as the US Patent database [29]. DeepWalk [52] and Node2Vec [23] have proposed using word embedding approaches for learning neighborhood features of nodes in a network graph. Word embedding approaches are also being used for a variety of semantic web applications, e.g., embedding RDF triples [53, 12] and encoding geo-spatial proximity [33]. Using latent feature vectors for data integration in knowledge databases has been explored in [61, 60].

**Relational Databases:** In the context of SQL, text capabilities, e.g., the use of synonyms, have been in practice for a while [14]. In the literature, techniques for detecting similarity between records and fields have also been explored. Semantic similarity between database records is explored in [32]. Phrase-based ranking by applying an IR approach to relational data appears in [40]. Indexing and searching relational data by modeling tupses as virtual documents appear in [41]. Effective keyword-based selection of relational databases is explored in [66]. A system for detecting XML similarity, in content and structure, using a relational database is described in [62]. Related work on similarity Join appears in [10]. Semantic Queries are described in [49]. Most recently, Shin et al. have described DeepDive [56] that uses machine learning techniques, e.g., Markov Logic-based rules, to convert input unstructured documents into a structured knowledge base.

The proposed cognitive database system can be distinguished by the following unique features: (1) Encoding relational data using word embedding techniques, (2) Using semantic vectors to enable a new class of SQL analytics queries (CI queries), (3) Ability to make contextual semantic matching, unlike the traditional value (syntactical) matching supported by current SQL queries, (4) Capturing relationship among multiple data types, including images, and (5) Ability of using external knowledge bases. Further, semantic vectors are primarily based on the database itself (with external text or vectors as an option). This means that we assume no reliance on dictionaries, thesauri, word nets and the like. Once these vectors are generated they may be used in vastly enriching the querying expressiveness of virtually any query language. These capabilities go far beyond analytical capabilities present in current relational systems. All well-known commercial and open source (e.g., Apache Spark [1], MADlib [25]) database systems have built-in analytics capabilities, e.g., Spark MLLib. Apache Spark can also create a deep-learning pipeline in which it can invoke an external deep-learning infrastructure e.g., TensorFlow [21] to train a model, and then load the trained model to perform inferencing operations [28]. However, such systems view databases as repositories for storing input features and results for the analytics or deep-learning frameworks. On the other hand, cognitive databases use the word embedding model to extract features from the database entities and use them to enhance its querying capabilities. Systems based on statistical relational learning models combine probabilistic graphical models and first-order logic to encode uncertain first-order logic rules based on known information [63]. In contrast, a cognitive database learns information about the relational data which is not known a priori.

7. CONCLUSIONS AND SUCCESS CRITERIA

In this paper we presented Cognitive Database, an innovative relational database system that uses the power of word embedding models to enable novel AI capabilities in database systems. The word embedding approach uses unsupervised learning to generate meaning vectors using database-derived text. These vectors capture syntactic as well as semantic characteristics of every database token. We use these vectors to enhance database querying capabilities. In essence, these vectors provide another way to look at the database, almost orthogonal to the structured relational regime, as vectors enable a dual view of the data: relational and meaningful text. We thereby introduce and explore a new class of queries called cognitive intelligence (CI) queries that extract information from the database based, in part, on the relationships encoded by these vectors.

We are implementing a prototype system on top of Apache Spark [1] to exhibit the power of CI queries. Our current infrastructure enables complex SQL-based semantic queries over multi-modal databases (e.g., inductive reasoning queries over a text and image database). We are now working on accelerating model training and nearest neighbor computations using a variety of approaches (e.g., using GPUs), and developing new techniques for incremental vector training. We believe CI queries are applicable to a broad class of application domains including healthcare, bio-informatics, document searching, retail analysis, and data integration.

7.1 Success Criteria

We believe Cognitive Databases are truly a new technology for incorporating AI capabilities into relational databases. As such it holds a great promise for innovative applications with a very different view of data as compared to today’s database systems. Since it is based on a new concept, there are no easy comparisons. For example, there are no relevant benchmarks except for ones used in NLP for testing language features such as analogies [45]. So, success of the cognitive databases will be mainly evaluated based on new applications within known domains (such as Retail), new domains of applications (such as medical drugs selection) that are currently in the sphere of AI-based systems, and the adaptation of CI capabilities as a standard feature by leading vendor as well as open source database systems. Finally, we hope this work spurs new research initiatives in this exciting emerging area in database management systems.
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