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Issue Article

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AUTOMATION OF DATABASE DESIGN AND DEVELOPMENT: FROM DOMAIN DESCRIPTION TO LOGICAL MODEL

***Abstract**: In the era of digital transformation, databases become key elements of information systems, underlining the importance of research in the area of their automated design and development. Particularly pertinent is the task of automating the creation of databases from textual descriptions of subject areas, considering the limited adaptation and availability of existing solutions for the Russian-speaking segment.*

The goal of this work is to develop a method for the automated designing of databases, adapted to Russian-language descriptions, combining theoretical analysis and practical development. The approach used includes natural language processing and machine learning technologies, enabling the automation of creating logical database models from structured and unstructured texts.

The research is theoretical in nature and thus does not involve the demonstration of working results. However, in the future, the results could demonstrate the efficiency of the proposed method in reducing the costs of database design, extending automation capabilities beyond the English-speaking context. This study makes a significant contribution to the automation methods of database design in the Russian-speaking segment.

The practical significance of the work lies in simplifying and accelerating database development, making the design process accessible to a wide range of specialists and paving the way for optimizing the creation of information systems.

***Key words**: relational database, natural language processing (NLP), structured query language (SQL), machine learning.*

***Language**: English*

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Introduction

In the context of the rapidly progressing digital transformation of various spheres of human activity, the role of databases as fundamental components of information systems has significantly increased. The foundational importance of databases for the efficiency, scalability, and accessibility of information systems heightens the relevance of research in their design and development. In this aspect, recognizing the automation of these processes as a strategically important tool allows for substantial reduction in costs associated with hiring specialized personnel and speeding up the development process.

Despite significant progress in the development of methods and technologies for automating database design, the issue of transforming descriptions of subject areas, formulated in natural language, into structured and optimized logical models remains particularly relevant. Most existing tools and approaches focus on the English-speaking sector, leading to insufficient adaptation and availability of solutions for the Russian-speaking professional community. Considering this imbalance, this study aims to contribute to the development of automation in the design and development of logical database models, focusing on the peculiarities of the Russian language.

The goal of this work is to analyze existing approaches to automatic database schema construction and to develop an original method adapted to the specifics of Russian-language descriptions of subject areas. This goal implies not only delving into the theoretical foundations of database design automation but also developing a new methodological tool, which represents a significant innovation in this field.

The structure of the article is organized as follows: the current part provides introductory information to immerse the reader in the problematics of the research. The second part conducts a detailed analysis of literary sources, identifying the potential and limitations of existing methods. The third part describes the proposed original method, including its conceptual foundations and algorithms. The concluding part is devoted to analyzing the obtained results, their significance, and practical application in various fields, as well as defining directions for further research.

Literature review

In the process of analyzing this topic, a review of achievements in existing scientific research in this area has been conducted, revealing a number of significant works. The found scientific efforts cover a wide range of components related to the automation of database design, including algorithmic models, instrumental tools, as well as methodological approaches to the conceptualization and transformation of subject areas into database schemas. Key themes in the research include studies dedicated to analyzing natural language descriptions for generating database schemas, developing unified data models, and the application of ontological methods in the design process. Let's take a closer look at the aforementioned works.

Geetha S. and Anandha Mala G. S. in their study [1] developed a methodology that allows converting natural English text into a structured representation of a database. Their approach is based on a knowledge extraction algorithm that begins with structuring the input data. This process includes extracting patterns from the data and their subsequent interpretation. The study emphasizes the importance of using natural language processing (NLP) technology for the effective automatic extraction of database entities and their attributes.

The authors also detail the process of identifying relationships, where the software requirements specification is interpreted in a Subject-Verb-Object format. This allows for the transformation of words into object-oriented attributes. A proprietary rule system is then applied to classify these attributes as classes, attributes, methods, and to define their relationships. The creation of rules, prioritization, and the use of training data help in the identification and classification of attributes based on their similarity to one another across different tables, after which each attribute is assigned a specific data type, ensuring the completeness and structure of the transformation into the database.

In the study [2], conducted by Sri Lalitha Y., Prashanthi G., and other group members, an approach to transforming natural language text into SQL code has been developed. The first stage of the text preprocessing process involves tokenization, lemmatization, and the removal of stop words to clean the original queries composed in English. The data undergo factorization using the Bayesian method, which aids in optimizing them for further analysis. The next step involves the development and application of a specialized named entity recognition (NER) model, aimed at extracting objects and corresponding tables from processed data. The retrieved entities are documented and stored in a dictionary for further use. The final stage includes transforming the processed data into SQL code using the Pypika and psycopg2 libraries, which allows for efficient integration of the original natural language query into the database structure.

The research work by Vadim Sheinin, Elahe Khorashani, and other scholars [3] focuses on developing a methodology for forming SQL queries using nested structures based on text composed in natural English language.

The study [4] conducted by Hafsa Shareef Dar, M. Ikramullah Lali, and other participants presents an analysis and comparison of various existing tools in the domain of transforming natural language text into SQL queries. The analyzed tools are categorized based on the use of three different methodological approaches: statistical, symbolic, and connectionist. It is important to emphasize that all tools reviewed are intended for use with text in natural English language.

The research by Wenjun Lin, Paul Babyn, Yan Yan, and Wenjun Zhang [5] focuses on developing a unique method for transforming the structure of a database into a natural language representation. The study provides a detailed description of an algorithm that follows a sequence of transformations: from XML to Contextual Modeling of Database Ontologies (COM-DB), then into Natural Language (NL), and subsequently into a query for GPT. Although this study does not fully align with the goals of our analysis, as it deals with the reverse process of transforming database data into natural language, it contains valuable sources that may be useful for the continuation of our work. In particular, the study mentions works dedicated to the application of natural language processing (NLP) methods for analyzing and interpreting user queries formulated in natural language.

In the research publication by V.A. Kozhevnikov and O.Yu. Sabinin [6], systems for the automated checking of open responses performed in natural language are analyzed, and criteria for these systems are formulated. The researchers developed a functional architecture of the system and examined the key aspects of its implementation. The Tomita-parser from Yandex, specializing in extracting information from texts, was chosen as the linguistic processor for the developed system.

Of particular interest in the context of our study are the grammatical rules developed by the authors for extracting entities from Russian-language texts, as well as the algorithm for analyzing responses, which is described in detail in the mentioned article.

Separate attention deserves the work by N.V. Gorbatov and O.Yu. Sabinin [7], which, similarly to the research by Geetha S. and Anandha Mala G. [1], covers a topic closely related to our research interests. However, a distinctive feature is that the system being considered does not process descriptions of subject areas but implements the transformation of queries formulated in natural language into SQL queries to the database. The authors present an algorithm that effectively translates sentences in natural language into structured queries.

Proposed methodology

The research has shown that texts describing subject areas can be divided into two main groups: structured and unstructured. Let us take a closer look at examples of these two approaches to description.

A structured description of a subject area is clearly defined and organized. For example:

"The entity Trading_Centers has the following attributes: Identifier, Size_of_Trading_Point, Rental_Cost, Utilities, Section, Floor.

The entity Shops has the following attributes: Identifier, Size_of_Trading_Point, Rental_Cost, Utilities, Number_of_Departments."

In contrast, an unstructured description uses a more free-form style of presentation. An example is:

"A trading organization conducts trade in commercial outlets of different types: shopping centers (SC) and stores.

SCs and stores may have such common characteristics as the size of the trading point, rental payments, utility services, and also specifics, for example, for SCs, this can be the indication of section, floor, etc., and for a store, the number of departments. Trading points can be located in different localities."

Based on this distinction, it is proposed to develop two approaches to the automation of designing and creating databases, corresponding to each type of subject area description. This will allow for the most effective transformation of the primary description into a logical database model, taking into account the features of structured and unstructured texts.

Let's examine in more detail the conceptual foundations and algorithms of the proposed approaches.

Automation algorithm for structured descriptions

As mentioned earlier, this algorithm is intended for structured input data. Below, the stages of the proposed algorithm are described:

1. Text processing of the subject area description. Analysis and preparation of text data for further parsing.

2. Tokenization. Breaking the text into individual words or phrases, which are then analyzed separately.

3. Lemmatization. Reducing words to their dictionary form to simplify analysis.

4. Extraction of entities, their attributes, and relationships using handwritten rules. Involves the application of developed algorithmic instructions to identify and categorize information.

5. Assigning data types to extracted entities. Necessary for the correct formation of the database schema.

6. Constructing DDL queries. Based on information obtained in previous stages.

7. Returning the resulting SQL in text format. Provides a ready-to-implement database schema.

The implementation of this algorithm places particular importance on the tokenization and lemmatization stages, during which it is suggested to use the Natasha library [8] – a modern tool for comprehensive natural language processing, specialized for the Russian language.

The Natasha library provides high-quality text segmentation into tokens and sentences, performs morphological and syntactic analysis, lemmatization, and extraction of named entities. In terms of functionality, Natasha is comparable to or exceeds similar solutions, while being available for use on the Python 3.5+ platform and PyPy3 without the need for a GPU, relying only on NumPy.

The algorithm for extracting entities, their attributes, and relationships is based on two key actions:

- Defining a pattern (regular expression) for searching the text;
- Subsequent searching for matches to the defined pattern.

The scheme of the overall algorithm for automatic database design based on the structured description of a subject area is shown in Figure 1.

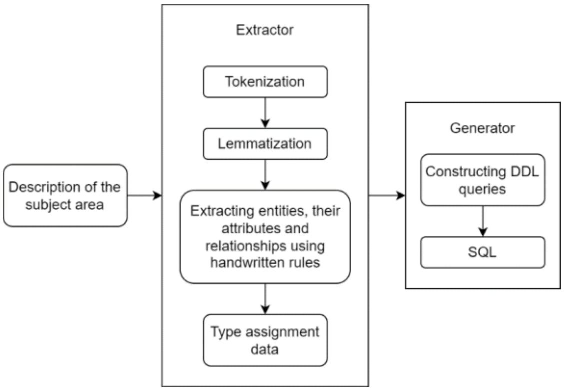

Figure 1 – Algorithm for automatic database design based on the structured description of a subject area

Thus, the developed algorithm represents a tool for automating the process of designing and developing databases, based on structured descriptions of subject areas. Integrating the Natasha library into the architecture of the presented algorithm facilitates the task of transforming the primary text description into a structured data format using tokenization and lemmatization methods.

However, it should be noted that the developed method is only suitable for a narrow range of tasks, as the entity extraction algorithm is based on regular expressions and is not adapted for texts with a differing content structure. For such cases, an automation algorithm for an unstructured description of the subject area, discussed further, is applicable.

Automation Algorithm for Unstructured Descriptions

This algorithm is applicable to a broader range of tasks, especially considering that the input data (subject area descriptions in natural language) are often presented in an unstructured form and may be formulated without the use of specialized terminology. This means that even a person unfamiliar with the concepts of entities, their attributes, and relationships in the context of databases can compose a description suitable for further processing. Solving the given task involves the implementation of machine learning methods.

General Actions Algorithm for Creating a Labeled Dataset and Training a Machine Learning Model:

1. Data collection (texts from which entities and attributes will be extracted). No open datasets were found during this research, however, faculty from the Saint Petersburg Polytechnic University of Peter the Great, represented by O.Yu. Sabinin, agreed to provide examples of coursework assignments containing descriptions of subject areas.
2. Data labeling. Manually marking primary keys (PK), foreign keys (FK), entities, their relations, and attributes using specialized software, doccano.
3. Data preparation for training. After data labeling, the data must be converted into a format that can be used for training the model. This usually involves converting annotations into a model-friendly format (e.g., BIO format for sequence tagging) and splitting the data into training and test sets.
4. Model selection for training. Models based on deep learning, such as LSTM (Long Short-Term Memory networks), BiLSTM-CRF (Bidirectional LSTM with Conditional Random Fields), or transformers like BERT and its adaptations for specific languages are often used for entity extraction.
5. Model training. Once the data is prepared and the model is chosen, the training process begins. Input data is fed into the model, which then attempts to learn from it, followed by an evaluation of its ability to correctly generalize data using the test set.
6. Model testing. After the model is trained, it's necessary to check how well it performs at extracting entities on new (test) data. Metrics such as precision, recall, and F1-score are used to evaluate model quality.

Originally, it was planned not to train a new model from scratch but to fine-tune the Natasha model, which has already been pre-trained on a large volume of textual data. However, considering that Natasha does not provide a direct API for retraining its models, it was decided to use another model, library, or framework that supports fine-tuning, such as BERT-like models.

In this case, the algorithm will slightly change:

1. Data collection.
2. Data labeling.
3. Preparing the fine-tuned model. To fine-tune a BERT-like model on your own data, you need to prepare the appropriate dataset, labeling entities, attributes, and connections within it. Then, following the documentation of the chosen library (for example, Hugging Face Transformers), carry out the fine-tuning process.
4. Using the fine-tuned model. After fine-tuning the model, it is necessary to use it to extract the required information from the text. The extraction results can be used as is or further processed using Yargy-based rules for cleaning or refinement. Yargy

is a tool for extracting structured information from natural language text using rules.

After extracting entities, attributes, and relationships between them, as in the algorithm for structured descriptions, it is necessary to construct DDL queries and return the resulting SQL code in text format.

Thus, this chapter has examined two key aspects of the proposed methodology for automating the design of databases: the automation algorithm for structured descriptions and the algorithm for working with unstructured descriptions.

Conclusions and further development prospects

In summary, the results of the research demonstrate that the developed method for automating database design from textual descriptions of subject areas in Russian is an effective means of reducing time and resource expenditures during the creation of information systems. This is confirmed by the successful adaptation of modern natural language processing and machine learning methods to the Russian-speaking context, as well as the demonstration of the practical applicability of the proposed approach.

The further development prospects are aimed at the practical implementation of the proposed algorithms in the software development industry. This could include integrating the developed method into existing database design tools, creating specialized applications for automatic data schema generation based on textual descriptions, and training professionals to effectively use this approach in practical projects.

The proposed algorithms have the potential to accelerate the processes of developing information systems, enhance their quality and accessibility, and reduce design stage costs. The realization of these prospects opens up new opportunities for the application of automated methods in the software development sector, contributing to the further advancement and optimization of information technologies.

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