

Programmed Test Script Generation from Natural Language Query

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Abstract: Development and Testing is a very important part of anything progression cycle. There exist different modules that ought to be attempted in a thing or programming after each build. Addition, change or abrogation of new methodologies requires thorough testing of the complete product. Test scripts are generated for the straightforwardness of testing. It is seen that a huge part of the procedures in test scripts are repeated. Converting natural language query into test scripts reduces the effort to the test engineer by finding relevant procedures in already existing database. The proposed system recognizes a trademark language query and changes over the inquiry into an executable test code using various NLP methodology. This paper get a handle on two techniques that are used to generate test script from Natural language query.

Index Terms: Natural Language query; Test Script generation; Intent Affirmation.

I. INTRODUCTION

Product Development Life cycle(PDL)involvesidea,research,development,testingandanalysisphases. Testing is a essential part where the thing advanced is tested for finish, execution and to find bugs. Testing is carried out after every build and also after every minor modification in the code. Testing involves test scripts written using scripting languages like Javascript, perl, python, Jscript etc. The test scripts are stored in a database and are run to test the complete thing. It has been seen that a huge part of the test scripts are duplicate codes. It is difficult to find relevant test scripts from the data base.

The continuous paper inspects an instrument where a Natural Language request association guide is given for the test expert toward enter the test requirement in the form of a Natural language sentence. The sentence is parsed to find the intent using intent recognition mechanism. Based on the intent, the relevant test scripts are identified and an executable test script is generated. This test script can be run to get the testing results.

II. EXISTING SYSTEM

A development system that creates a movement from natural language texts, for instance, film items or stories was developed. The structure does semantic assessment to find the motion cuts considering activity words [9]. Advancement associating with the creation of PC informational index systems and the scrutinizing of data contained in that was done in . The means involved generation of a fact tree based on natural query, check query for semantic precision and produce question for the database. Conversion of business rules written in natural language to a set of executable models as UML, SQL, etc was finished in. Intent recognition involves finding the intent of the sentence close by disputes. The phony legs have three locomotion modes walking, stair ascent and stair decent. The locomotion intent of the subject is identified using SVM[.

Discussion about the conspicuous verification of human reason in setting of human-robot coordinated effort. Secret Markov Models (Very much been acclimated with portraying limited amounts of gestural patterns. They think about the remarkable circumstance. Relating the context and history of coordinated effort to the kinematics is a keypoint for seeing human movements in HRI. A comparative study of cloud platform to develop Chabot is discussed. User input is taken care of through two modules: plan classification and entity recognition. External APIs and algorithms are used to make response .

Language Sorting out Shrewd Help (LUIS) helpsto make models for the applications to all the more promptly handle the intents or entities. LUIS helps developer to build applications that can understand human language and react to users accordingly. It supports various languages such as English, German, Italian and French. The advantage of LUIS is that one need not have to worry about explicit tokenization.

III. PROPOSED SYSTEM

The plan of the structure is isolated on the reason of requirement in the order of execution. This allows the architecture to expect an extraordinarily specific development consisting of extraction, pre-dealing with, building ability signatures, mapping and parameter extraction.

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The first main module as shown in Figure 1 of the architecture incorporates a parser that is used to parse a variety of capacities and perceive comments, both single and multiline. It also extracts the same and utilizes it to populate a database of capacity.

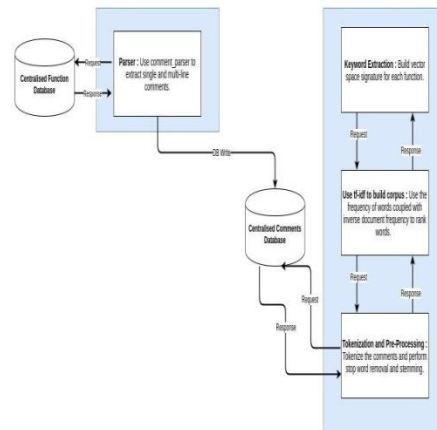


Fig.1: High level system architecture-Parsing and Keyword Extraction

The accompanying piece of the designing revolves around extracting keywords and uses various models to help with building a corpus of words that help with pre-taking care of. This module similarly interacts with the database to access the previously populated function list. This module closes with building a vector signature for each capacity in the informational index, which is made as striking as possible. Important keywords in text is determined by TF-IDF method. It picks the important words in a document, where

$$tf_{i,j} = \frac{\text{total number of occurrences of } i \text{ in } j}{\text{total number of documents containing } i}$$
$$df_i = \frac{1}{\text{total number of documents containing } i}$$
$$N = \text{total number of documents}$$

The accompanying piece of the designing is more client/client facing in nature as shown in Figure 2. It engages the client to pass a query as Normal language. The above mentioned pre-taking care of is moreover performed on the client input. A similar vector signature is built.

The next module of the architecture is the crucial part of the function arranging that utilizes various models to design the vector characteristics of commitment to the ongoing vector signature database.

In another technique, LUIS APIs are used to bring the intent of the given sentence with the entities. Language Understanding Intelligent Service (LUIS) [15] helps to create models for the application to better understand the intents or entities. LUIS is a toolset and runtime application for the generation and execution of fundamental language understanding models. It has two chief parts, Component Extraction, to extract an expected keyword, and Intent Resolution to determine whether a given word matches a pre-specified intent. There are generally two level association focuses, the Registrar, which gives APIs to select and dispense with models, and the runtime core which provides language understanding facilities.

The Recorder surfaces two clear APIs, but internally contains reasoning to copy model data into within database, serialization and deserialization logic, and multithreaded initialization of Executors.

The Specialist detaches the LUIS Programming point of interaction limit as taken from the server bunch with the objective that the LUIS codebase did not require colossal changes while being moved from the server to on-device. It directly wraps the LUIS APIs for Entity Extraction and Logistic Regression and ensures the data provided to the LUIS APIs are in the format expected [15].

The client given request is transported off LUIS using APIs to get the intent and its components. This is intended to the watchwords obtained from the test abilities. The matched test scripts are changed over totally to executable code as shown in figure 3.

IV. RESULTS AND ANALYSIS

The association point (GUI) built grants the client to really enter natural language input. The text enclosed fills as a medium to enter the data. In Figure 4, 5, 6 different kinds of data is provided. This is an intuitive mark of association for engineers. In Figure 4 the client enters the request. This request sends a post request to the server. The flask server responds by performing the required translation and forming the capacity call to the source file.

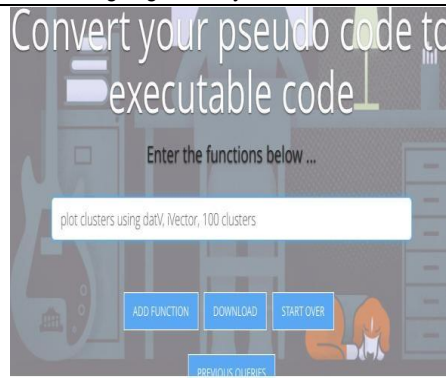


Fig.2: Entering second function and clicking on ADDFUNCTION button



Fig. 3: Content getting downloaded

In figure 7 the client downloads the last happy that is generated. This can be gotten to from the downloads folder. This is ready to execute, "source archive" is the last converted script.

V. CONCLUSION

Making test scripts is a drawn-out endeavor and manytimes it's repetitive. The gadget changes over a Trademark language query into executable test script. The above tool uses TF-IDF method and LUIS built-in API to get the intent of the query. It has been observed that intent recognition works better than the repeat methodology. The gadget not simply helps decline in redundant code but also makes the testing process faster.

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