

Impact of delete and update queries on DBEst++
approximate query processing engine

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Chapter 1

Project Progress report I

1.1 Project objectives and motivations

The general sub-domain which the project is based on is the **AI- Enabled data Management**. The category that this project comes under is **The extended system with additional components (category-3)**

The major objectives this project is as follows:

1. Include the functionalities of the delete and update queries by feeding the engine with series of delete and update queries.
2. Analyze the engine once these new functionalities have been embedded and analyze the behaviour of this engine by calculating the relative error and response time. The relative error is the found by identifying the difference between the predicted answer from the model and the actual answer expected. This can be in the form of mean squared error.

$$\text{rmse} = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^n (y_i - x_i)^2} \text{ where } n \text{ is the total number of data, } y \text{ is the actual label and } x \text{ is the predicted label}$$

The response time is found out by taking the starting time in which the query goes into the model and the ending time when the result comes out of the model and finding the difference between both.

3. If the existing approach does not work well for the new set of functionalities we try to suggest the possible change in the algorithm within the engine.

The reason that our project falls under this category is because our aim is to add the functionalities of delete queries and update queries and analyze how the DBEst++ engine behaves to these kind of queries because these queries has not been analyzed on the previous work. Based on the analysis we will try to modify the algorithm within the engine if it does not work well for these new set of functionalities.

1.2 Literature Review

The tuning of queries and other parameters in a database management system has been a recent topics of research. It has been proved that Machine Learning has been in help in providing effective results in tuning the parameter for the database (Van Aken et al., 2017). One of the functionality that the database looks for is the approximate query processing. The approximate query processing is the way of predicting the results of the query even before the query is executed in the database. In recent years many such query processing engines have been developed. Some of the popular engines are DBEst (Ma and Triantafillou, 2019) and DeepDB (Hilprecht et al., 2020).

In DBEst the workflow is that queries are sent to the DBEst engine and the samples are done and later they are used to regression model and the density estimator. Sampling is the first process to be done over to group the data. scikit-learn packages (Grid Search CV) is used to tune the models by using cross-validation. However, the choice of an appropriate regression model is complex because Different models work better for different data regions. For the implementation the models used are XGBoost, and GBoost. First, each model is trained separately. Subsequently, the accuracy performance of each of these models is evaluated, using random queries over the independent attribute's domain. Also kernel density estimation is chosen as it can be performed in any number of dimensions which allows the

DBEst support multivariate query processing.

Both these engines uses Machine Learning algorithms in order to predict the answer to the queries given. In the case of DBEst the machine learning models like kernel density estimator and regression models have been used. In the case of DeepDB the Relational sum product networks has been used. Despite the success of these models in terms of accuracy and efficiency, there was scope of more improvements that can be done in terms of accuracy, response time and memory overheads.

These improvements were made by extending the work of DBEst model called the DBEst++ (Ma et al., 2021). This engine used Mixture Density Network (MDN) for predicting the answer to the queries. This network is mainly used in this article due to its large success in several real world applications (Graves et al., 2016). There are two types of MDN models to be used in DBEst++. The MDN-regressor is used for regression tasks and the MDN-density is used for density estimation. The structures of the networks are the same for MDN-regressor and MDN-density. MDNs are simple and straightforward - one of the main reasons it was selected. Combining a deep neural network and a mixture of distributions creates a MDN model.

Machine Learning methods can only operate on numerical or continuous data. Binary, ordinal encoding methods are usually used for converting the variables into the required numerical or continuous form. These encoding methods map categorical values into arrays of 0 and 1s, and since the output is numerical, they can be used in all machine learning methods. So a conversion method called the skip gram model is used in this article due to its huge success with words and its combinations (Mikolov et al., 2013). Skip Gram model is used to transform group attribute values and other categorical attributes into a real valued vector representation. As categorical attributes have no meaningful distance between successive values learning a relationship between a categorical independent variable and a dependent one is very difficult. Using word embedding introduces such a meaningful distance between different independent categorical-attribute values becomes easier and more

accurate. With all these methods into the workflow of DBEst++ it was proved from this article that DBEst++ was much better model in terms of accuracy, response time and memory overheads.

1.3 Work Completed

1.3.1 System Architecture

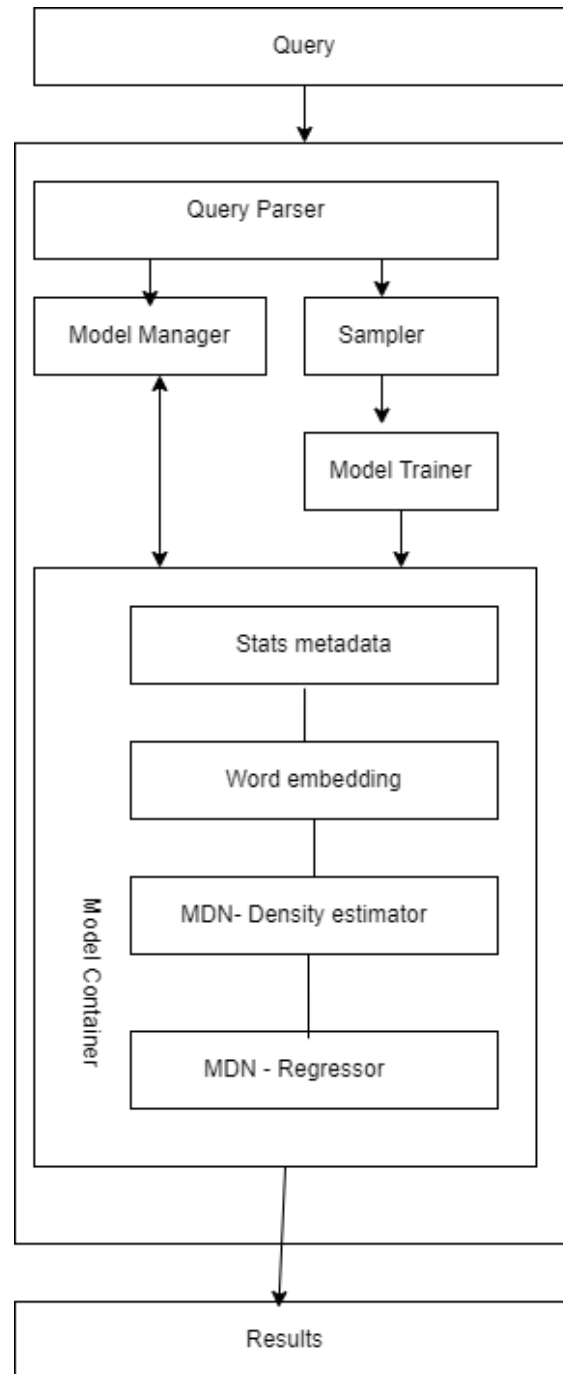


Figure 1.1: System architecture for DBEst++

1.3.2 The components of the system architecture that is completed

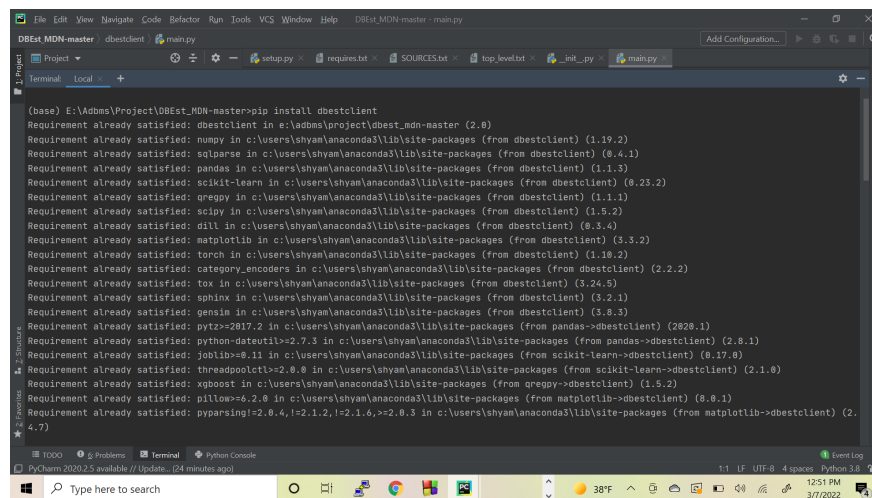
The **Query Parser** parses the incoming query and check if the incoming query is the selection queries or insert queries or update queries or any creation queries.

The **Model Manager** selects the appropriate model from the Model Container which is in this case will be word embedding or mixture density network which will use on the query and if the query is the select statement it will also select the data from the range of variable values specified. These representative values are used in the model to approximately evaluate the results of the query.

The **Sampler** create samples of tables, based on which Machine learning models will be built. The **Model Trainer** module trains word Embedding and Mixture density network (MDN) models upon the drawn samples from the sampler.

The **Model Container** maintains the metadata and the models which will be used upon the query. The models used for DBest++ are Word Embedding and Mixture Density network which again divided into two classes MDN- Density estimator and MDN - Regressor.

Since all these components are set once the DBest++ environment used is setup which is given in github as open source we have setup the environment successfully and the screenshots supporting the successful installation of DBest++ environment.



```
(base) E:\Adhms\Project\DBest_MDN-master>pip install dbestclient
Requirement already satisfied: dbestclient in e:\adams\project\dbest_mdn-master (2.0)
Requirement already satisfied: numpy in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (1.19.2)
Requirement already satisfied: sqlalchemy in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (0.4.1)
Requirement already satisfied: pandas in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (1.1.3)
Requirement already satisfied: scikit-learn in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (0.23.2)
Requirement already satisfied: gregpy in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (1.1.1)
Requirement already satisfied: scipy in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (1.5.2)
Requirement already satisfied: dill in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (0.3.4)
Requirement already satisfied: matplotlib in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (3.3.2)
Requirement already satisfied: torch in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (1.10.2)
Requirement already satisfied: category_encoders in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (2.2.2)
Requirement already satisfied: tox in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (3.24.5)
Requirement already satisfied: sphinx in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (3.2.1)
Requirement already satisfied: gensim in c:\users\shyam\anaconda3\lib\site-packages (from dbestclient) (3.8.3)
Requirement already satisfied: pytz=2017.2 in c:\users\shyam\anaconda3\lib\site-packages (from pandas->dbestclient) (2020.1)
Requirement already satisfied: python-dateutil<2.7.3 in c:\users\shyam\anaconda3\lib\site-packages (from pandas->dbestclient) (2.8.1)
Requirement already satisfied: joblib>=0.11 in c:\users\shyam\anaconda3\lib\site-packages (from scikit-learn->dbestclient) (0.17.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\shyam\anaconda3\lib\site-packages (from scikit-learn->dbestclient) (2.1.0)
Requirement already satisfied: xgboost in c:\users\shyam\anaconda3\lib\site-packages (from gregpy->dbestclient) (1.5.2)
Requirement already satisfied: pillow<6.2.0 in c:\users\shyam\anaconda3\lib\site-packages (from matplotlib->dbestclient) (8.0.1)
Requirement already satisfied: pyparsing<2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in c:\users\shyam\anaconda3\lib\site-packages (from matplotlib->dbestclient) (2.4.7)
```

Figure 1.2: Screenshot 1

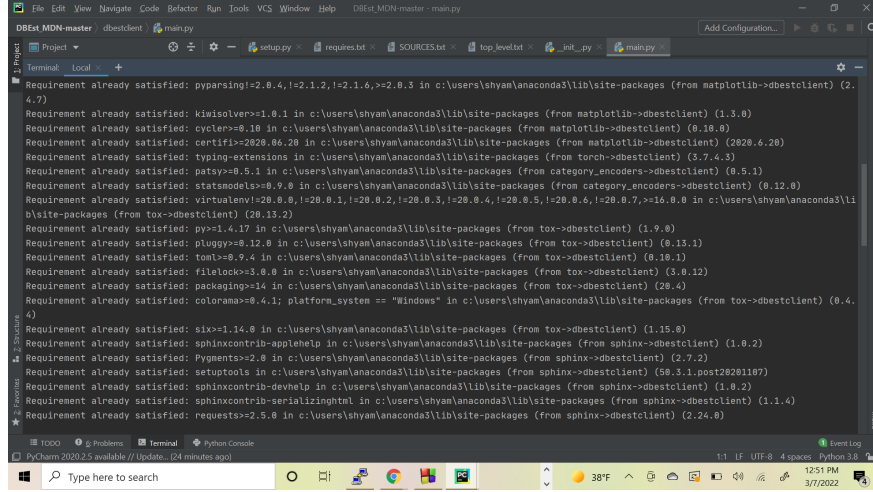


Figure 1.3: Screenshot 2

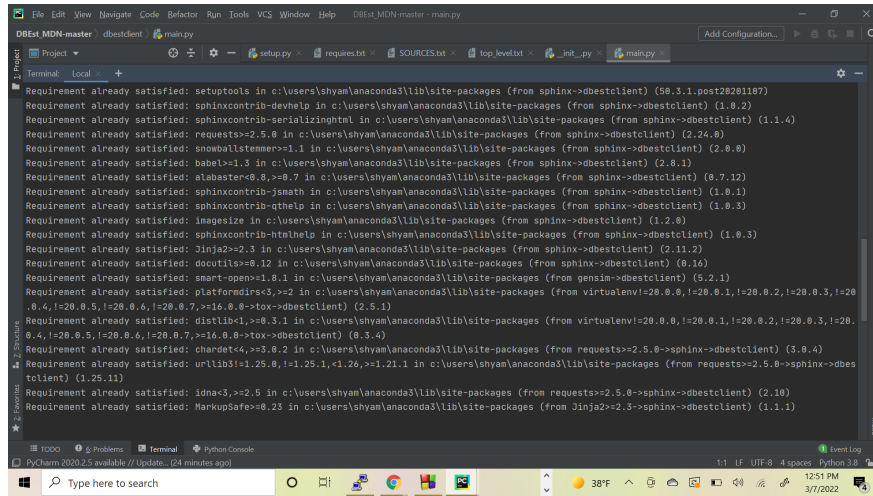


Figure 1.4: Screenshot 3

1.3.3 Project schedule status

As mentioned in the time table the data has been collected which was already provided from the people who has created the DbEst++ architecture. The data are the Filght data and TPC-DS. The intital setup of the architecture is also accomplished as it can be seen in the screenshots provided above. The only part we couldn't complete was implementing the word embedding and MDN model since it has some issues with the version and we are currently figuring it out.

1.4 Work to be done and Time Table

The word embedding model used in this architecture is the **Skip Gram model**. Skip Gram model is used to transform attribute values and other categorical attributes into a real valued vector representation. As categorical attributes have no meaningful distance between successive values learning a relationship between a categorical independent variable and a dependent one is very difficult. Using word embedding introduces such a meaningful distance between different independent categorical-attribute values becomes easier and more accurate.

For example, let us consider the salary information of staffs in a university. Let us consider Tom and Alan are given almost the same salaries let us in this case consider 80-83k per year. Therefore the embedding vectors for Tom and Alan will be similar.

To use this approach, the training data has to be prepared by using natural language processing methods. In this case, the data is in form of rows in the table. When preparing the training data the dataset is created in such a way that pairs of categorical attributes values comes together in a row of the table. These pairs are given to the Skip Gram model which tries to find similar vector representations. To create the training pairs, the attributes that are involved in the query is used. If the involved attributes are not categorical, it is then discretized first. Furthermore, it is possible that a distinct value exists in two different attributes, so to avoid pushing wrong information to the Skip Gram model, a prefix for each distinct value in the attributes is added. For example in value Tom of the attribute name it will be prefixed as "name Tom".

For example we have a query where the staff information has to be grouped by with respect to their department in which they are working on. For density estimation in the **MDN- density estimator** the input features that are sent are the word embedded data or vectorized data of the information that are selected to display. The label or the result expected would be the categorical attributes given after the WHERE command. The density

estimator aims in finding the distribution of the categorical attributes across the grouping done in this example mentioned.

For regression estimation in the **MDN - regressor** will take the inputs features as the word embedded data or vectorized data of the information that are selected to display and the categorical attributes given after the WHERE command. The label will be the resultant answer to the given query. The regressor aims at finding the average resultant values for the group using the input features.

After creating these models we will be running it on the data which is the set of queries collected and run it on the model. The model is benchmarked through analysis which is done through by finding the relative error and response time. The relative error is the found by identifying the difference between the predicted answer from the model and the actual answer expected. This can be in the form of mean squared error.

$$\text{rmse} = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^n (y_i - x_i)^2}$$

where n is the total number of data, y is the actual label and x is the predicted label.

The response time is found out by taking the starting time in which the query goes into the model and the ending time when the result comes out of the model and finding the difference between both.

Now once these initial analysis are done now we have to extend this architecture for update, delete and even for complex queries by making changes into the MDN network since this network is responsible for prediction of the answers for the queries fed in. Once these changes are made it analyzed again with respect to the relative error and response time.

The time table for the rest of the project is as follows

Tasks	Starting date	Ending date	Deliverables	Person-in-charge
Report Preparation	02/28/2022	03/07/2022	Submit report	Shyam, Ramya
Run DBEst++	02/21/2022	02/28/2022	Knowing DBEst++	Shyam
Vectorize data	03/07/2022	03/14/2022	Data to train	Ramya
Run DBEst++	03/14/2022	03/21/2022	DBEst++ new results	Shyam
Report Preparation	03/21/2022	03/28/2022	Submit report	Ramya, Shyam
Analyze results	03/28/2022	04/06/2022	Results compared	Shyam
Improving algorithm	04/06/2022	04/13/2022	Achieving objective	Shyam, Ramya
Rerun algorithm	04/13/2022	04/19/2022	Executing objective	Shyam, Ramya
Analyzing algorithm	04/19/2022	04/26/2022	Analyzing objective	Shyam, Ramya
Final Report	04/26/2022	05/02/2022	Submit report	Shyam,Ramya
Final Presentation	04/26/2022	05/02/2022	Presentation	Ramya,Shyam

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