<table>
<thead>
<tr>
<th>Title</th>
<th>An efficient customer search tool within an anti-money laundering application implemented on an international bank's dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors(s)</td>
<td>Le-Khac, Nhien-An; Markos, Sammer; O'Neill, Michael; Brabazon, Anthony; Kechadi, Tahar</td>
</tr>
<tr>
<td>Publication date</td>
<td>2009-07-16</td>
</tr>
<tr>
<td>Conference details</td>
<td>2009 International Conference on Information and Knowledge Engineering (IKE'09), Las Vegas, USA, 13-16 July 2009</td>
</tr>
<tr>
<td>Link to online version</td>
<td><a href="http://www.worldacademyofscience.org/worldcomp09/ws/conferences/ike09.html">http://www.worldacademyofscience.org/worldcomp09/ws/conferences/ike09.html</a></td>
</tr>
<tr>
<td>Item record/more information</td>
<td><a href="http://hdl.handle.net/10197/7846">http://hdl.handle.net/10197/7846</a></td>
</tr>
</tbody>
</table>
An efficient customer search tool within an Anti-Money Laundering application implemented on an international bank’s dataset

Nhien-An Le Khac\textsuperscript{1}, Sammer Markos\textsuperscript{1}, Michael O’Neill\textsuperscript{1}, Anthony Brabazon\textsuperscript{1} and M-Tahar Kechadi\textsuperscript{1}

\textsuperscript{1}School of Computer Science & Informatics, University College Dublin, Dublin, Ireland

Abstract

Today, money laundering (ML) poses a serious threat not only to financial institutions but also to the nations. This criminal activity is becoming more and more sophisticated and seems to have moved from the cliché of drug trafficking to financing terrorism and surely not forgetting personal gain. Most of the financial institutions internationally have been implementing anti-money laundering solutions (AML) to fight investment fraud activities. In AML, the customer identification is an important task which helps AML experts to monitor customer habits: some being customer domicile, transactions that they are involved in etc. However, simple query tools provided by current DBMS as well as naive approaches in customer searching may produce incorrect and ambiguous results and their processing time is also very high due to the complexity of the database system architecture.

In this paper, we present a new approach for identifying customers registered in an investment bank. This approach is developed as a tool that allows AML experts to quickly identify customers who are managed independently across separate databases. It is tested on real-world datasets, which are real and large financial datasets. Some preliminary experimental results show that this new approach is efficient and effective.

1. Introduction

Money laundering (ML) is a process of disguising the illicit origin of "dirty" money and makes them appear legitimate. It has been defined as "... to knowingly engage in a financial transaction with the proceeds of some unlawful activity with the intent of promoting or carrying on that unlawful activity or to conceal or disguise the nature location, source, ownership, or control of these proceeds" [Genzman]. Through money laundering, criminals try to convert monetary proceeds derived from illicit activities into “clean” funds using a legal medium such as large banks, investment or pension funds. This type of criminal activity is getting more and more sophisticated and seems to have moved from the cliché of drug trafficking to financing terrorism and surely not forgetting personal gain. Today, ML is the third largest “Business” in the world after Currency Exchange and Auto Industry. According to the United Nations Office on Drug and Crime, worldwide value of laundered money in a year ranges between $500 billion to $1 trillion [Baker] and approximately $400-4500 Billion associated with drug trafficking. These figures are at times modest and are partially fabricated using statistical models, as no one exactly knows the true value of money laundering, one can only forecast according to the fraud that has already been exposed. Nowadays, it poses serious threat not only to financial institutions but also to the nation. Some risks faced by financial institutions can be listed as: reputation risk, operational risk, concentration risk and legal risk. At the society level, ML could provide the fuel for drug dealers, terrorists, arms dealers and other criminals to operate and expand their criminal enterprises. Hence, the governments, financial regulator or Irish Financial Services Regulatory Authority (IFLSRA) requires financial institutions to implement processes and procedures to prevent and detect money laundering and the financing of terrorism and other illicit activities that money launderers are involved in. So, anti-money laundering is of critical significance to national financial stability and international security.

Typically, an AML system is composed of some components such as: interface, customer identification, transaction monitoring, case management, reporting system, etc. Among them, customer identification is one of the most important tasks as it assists AML experts monitoring customer habits: some being
customer domicile, transactions that they are involved in etc. Fundamentally, a customer is identified by a searching task performed on customer databases with query tools provided by DBMS. However, in the case where a specific customer is stored in separate multiple databases that are managed independently, then this approach would cause a performance impact in searching time. Users need firstly to login in to the different databases, run the same query repeatedly and get the searching results discretely i.e. they are displayed independently. Furthermore, in large financial institutions, there are many databases that have a very complex design. This sort of approach allows great flexibility however it does impact the performance heavily. Besides, data quality is also another factor that makes this naïve search approach becoming unfeasible and/or a time-consuming task.

In this paper, we present a new approach for identifying customers registered in an international investment bank BEP\(^1\). This approach provides a global view of customer information and it is developed as a tool that allows users to quickly and efficiently identify customers who are managed independently across separate multiple databases. This tool is a component of an AML solution developed in a collaboration project between University College Dublin and BEP.

The rest of this paper is organised as follows: the section 2 is a background composed of two main parts. The first one deals with the current status of BEP’s datasets and their customer search problems within the AML context. Some indexing approaches for data search in the literature are discussed in the second part. Next, we present our new approach that is a global indexing based on word-ordered grouping and inverted list in the Section 3. We describe the implementation of this approach in section 4. Section 5 presents preliminary experiments of this customer search approach. Finally, we conclude in section 6.

2. Backgrounds

We start this section with a brief presentation of an AML project at BEP and then we will discuss on customer search problems in its current environment. We finish this section by reviewing some indexing approaches for data search in the literature.

\(^1\) Real name of the bank can not be disclosed because of confidential agreement of the project. BEP, which is one of world’s largest banks (top ten), has about 300,000 employees managing 200 million customer accounts across six continents in more than 100 countries.

2.1. AML in BEP

Similar to any banking transaction, BEP is required by law to conduct strict AML governance on all transaction. The BEP AML Unit does not have an automated solution to support pattern recognition and detection of suspicious activities. The purpose of this project is to apply new principles and methodologies to build an AML framework in order to detect suspicious customer transactions and behavior for the AML Unit of BEP. In this framework, one of the important components is customer identification. Before launching any customer transactional investigation, the customer should be identified in all customer databases of BEP. As mentioned above, in a simple case, it can be carried out through queries provided by current DBMS. However, the structure of BEP’s databases is complicated and there are also problems with data quality that will be analyzed and discussed in the section 2.2 below.

2.2. BEP Datasets and Customer Search

BEP datasets are divided in 16 different environments corresponding to 16 clients with multiple funds per client and managed hence by sixteen independent databases. When a new customer or an investor X want to invest into a specific fund (client specific), the AML team would request certain documentation and will always treat him as a new customer even though he could invest into one/more of the other 15 clients, i.e. already exist in another databases. The purpose of customer search is to verify and identify a customer’s profile in all invested funds. Currently, a manual search is applied by the AML Unit based on DBMS queries. However, this is a time-consuming task because users should login separately on each database and carry out repeated queries. Moreover, each database contains not only data but also its meta-data so many joint operations are needed to retrieve the information required.

Meanwhile, data quality is also another performance impact that affects the searching task. BEP’s input GUI is not efficient and its databases design is cumbersome. Each customer database is “identical”, i.e. the customer identification (CID) is only unique in this database but the CID is not unique in all databases. For instance, we can have (name= “John Smith”, CID= “12345”) in database A vs. (name= “Peter Chang”, CID= “12345”) in database B. Briefly, there is a uniqueness violation at the global level. Furthermore, each database has a different set of quality problems at the instance level. Some problems can be listed as:
- missing values, dummy values or null. It would happen in most of data fields in all databases except the CID, the customer type (corporate, individual and joint) and the fund name.
- abbreviations, e.g. “A/C” vs. “AC” and “Account”.
- word transpositions e.g. “John Smith” vs. “Murphy John”
- duplicated records, e.g. “John Smith” vs. “J. Smith”

Moreover, the name of some corporate customers is normally not identical even though they are the same company. For instance, “First Commercial Bank Ltd”, “First Commercial Bank Ltd OBB Account”, “First Commercial Bank Ltd Trust Account TA 101010”, “First Commercial Bank Ltd Trust Account TA 505055”, etc. We call this a “company name group” property. Besides, some customer databases also have the problem of incoherent data in address data fields. Concretely, address information includes the following data fields: “Street”, “Town”, “Zip”, “Country Code” and “Country”. And then, for example, the “Zip” field contains information about the street, house number and/or town, city instead of its zip code.

Because of the customer datasets quality problems as well as its complicated design, the manual customer search task by DBMS queries currently takes more than two hours to identify a customer.

### 2.3. Indexing

Fundamentally, search engines index data collected to facilitate fast and accurate information retrieval. Some indexing methods in literature are tree-based, suffix tree, inverted list, citation index, ngram index, term document matrix, etc. Tree-based index would be the most popular method where searching data are linked with tree nodes. Tree topology can be varied from binary [Knuth] to B-Tree family such as B/B*/B+-Tree [Bayer1][Bayer2][Topsist]. For instance, some DBMS implement their index structure based on B-Tree such as MySQL, SQL Server [Sheldon]. Nevertheless, this topology is not efficient for indexing complex and/or bad quality data fields.

---

2 Again, due to the confidential agreement, all examples presented in this paper do not use the real customer names, company names and address.

Suffix tree [Giegerich], so-called PAT tree or position tree, is a data structure which presents a given string in a suffix way (Figure 1). The suffix tree for a string S is a tree whose edges are labeled with strings such that each suffix of S corresponds exactly one path from the tree’s root to a leaf. The advantage of suffix tree is that operations on S and its substring can be performed quickly. However, construction suffix tree takes time and storage space linear in the length of S.

Inverted list [Zobel1] is another kind of index where each entry in the index table includes two elements: an atomic search item and a list of occurrences of this item in whole searching space. For example, the index of a book lists every page on which certain important words appear. This approach is normally implemented by the hash table [Corman] or binary tree [Knuth]. Inverted list is one of the most efficient index structures [Zobel2].

Citation index approach [Garfield] stores the citation or hyperlinks between documents to support citation analysis. This approach is normally applied in the Bibliography domain. Ngram index [Google] stores sequences of length of data and term document matrix stores the occurrences of words in the documents in a two-dimensional sparse matrix. The last two index methods are mainly used in information retrieval or text mining [Feldman].

### 3. Customer Search approaches

As mentioned above, the customer search can be carried out by DBMS queries. However, the performance of this approach depends strongly on the quality of data sets. Therefore, the current quality of BEP’s customer data sets should be improved before running any query. For instance, in order to correct the misspelling problem, a spelling module basing on statistic of typo and phonetic errors of customer data sets should be implemented. Similarly, abbreviation words must be normalized, e.g. “A.C”, “Account”,

![Figure 1. A suffix tree for “bananas$”](image)
“A/C.” are transformed to “A/C”. Meanwhile, data mining techniques such as decision tree induction, regression, and inference-based tools can be applied to fill missing values (tuples that contain missing value fields can no be ignored because all customer information are important). Indeed, in some cases, we should fill the missing value manually. Similarity, the word transposition and duplicated record problems often need manual intervention. Besides, the incoherent data problem in address data fields (Section 2.2) can only be manually corrected but it is an unfeasible task with large datasets. Briefly, a general solution for improving efficiently the quality of BEP’s customer data sets is still an open question. Last but not least, the execution of DBMS queries on 16 independent BEP’s customer databases is also a highly time-consuming task. Next, we present our approach which can overcome the quality and design problems of BEP’s customer databases.

3.1. Basic concepts

In this new approach, we aim to provide a global view of information about all customers managed independently across 16 BEP’s customer databases. Concretely, we build a global index of these customers and provide a search engine for AML users. Firstly, by analyzing BEP’s customer datasets, some important features can be resumed as:

- There are two main types of customer: individual and corporate.
- The individual customer has two name fields: “First Name” and “Last Name”. In some records, “First Name” (or “Last Name”) field stores all parts of customer name; e.g. in a record X, “First Name” field stores “John Smith” and its “Last Name” is empty. This is a special kind of missing value.
- The corporate customer only has one name field: “Company Name” and most of them has a “company name group” property as mentioned in the Section 2.2 above.
- “Country” field is the most popular data, i.e. its missing value is less than 1%.

Besides, we also build a summary of all abbreviation cases after this analyzing process. We then build our solution based on the attention of these features and on the assuming that all abbreviation words are normalized as well as all minor data preprocessing are performed.

In order to deal with the incoherence of address data (Section 2.2), we merge all of address data fields in one field called “Address”. Similarity, we merge the “First Name” and “Last Name” of individual customer into one field named “Customer Name” to solve the missing value problem. For each data record, word-order in “Address” and “Customer Name” can be varied. For instance, we can have “John Smith” vs. “Murphy John” or “123, Main Street” vs. “Main Street, 123” (word transposition problem). Therefore, the inverted list technique can be used in this case to index “Address” and “Customer Name”.

Meanwhile, the word-ordered in the “Company Name” field is important because of the “company name group” property. Therefore, we need another type of index in this case. We can address the “company name group” as a kind of suffix problem and we can then use the suffix-tree topology. Nevertheless, the implementation of this topology is complicated. Hence, we base on this topology to build an index tree which is simpler than the suffix tree for the “Company Name” field of BEP’s customer datasets. Briefly, our global index is composed of three main parts: “Company Name” index, “Customer Name” and “Address” index based on tree topology (the first index) and inverted list (the last two ones) that will be detailed in the following section.

3.2. Index architecture

The main architecture of our index consists of “Company Name” tree, “Customer Name” and “Address” inverted lists (Figure 2, 3 and 4). Furthermore, the whole customer datasets are grouped by the customer type (corporate or individual) and the country.

![Figure 2. An example of CN tree index](image)

3.2.1. “Company Name Tree” (CN tree) design. This is a suffix tree based topology. Generally, the first word
of a company name appears in the root level (level 0) and its last word is in the leaf level (Figure 2). The CN tree includes a set of nodes. There is only one node at the root level. Each node contains one or many elements and each element at level l links to only one node at level l+1 or to NULL if l is the leaf level. Each element has a key which is a word from the "company name" string. Hence, each node p at the level l (l>0) contains all words derived from their prefix word at the level l-1 and so on. Formally, supposing that BEP’s customer datasets includes a set of n company names N and each company name cn_i ∈ N (i=1, 2 ... n) is a string composed of a set of words w_j and the number of words w_j in a cn_i is noted as C_i. A CN tree T of N from customer datasets is defined as:

- The height of T is h, h=max(C_i), i=1,2...n
- ∀ node p_l ∈ T, p_l ⊇ set of elements {em}: Card({em})>0, em = w_j.
- The root at level 0 has at most one node p_0.
- Each element em0, ∈ p_0, em0 contains the first word of each company name cn_i.
- ∀ element em ∈ T at the level l (l ≥ 0 and em is not at the leaf level), there is a link, so-called node-link, between em and a node p_em ∈ T at the level l+1. The node p_em contains first word of all suffixes of the word w_j stored in em.
- A path from the root to the leaf by following node-links will create a specific company name. Each element at the leaf level does not have a node-link but a list of (client identification (FID), customer identification (CID)) of company name that creates this path.

For instance, as shown in the Figure 2, we have the following company name: “FIRST COMMERCIAL BANK LTD”, “FIRST BANK LTD OBB ACCOUNT”, “FIRST AMERICA BANK LTD TRUST ACCOUNT TA 101010”, “FIRST AMERICA BANK LTD TRUST ACCOUNT TA 505055”, “ABC CAPITAL GROUP”, “ABC CAPITAL NEW YORK BRANCH”, “BANK OF UBUBA” and “INTERNATIONAL DDD INVEST CORP”. Hence, the root node has four elements: em0 = “ABC”, em0_l = “BANK”, em0_2 = “FIRST” and em0_3 = “INTERNATIONAL”. The element em0_l links to a node that has one element “CAPITAL” at the level 1. Then, this element links to another node that has two elements: “GROUP” and “NEW”. The element “GROUP” is at the leaf level, it then contains {“Skada”, “B123”} (list of {FID, CID} has only one element). Otherwise, the element “NEW” links to another node at the level 2, etc. The path from the root node with the element “ABC” following its node-links creates two company names “ABC CAPITAL GROUP” and “ABC CAPITAL NEW YORK BRANCH”. Similarly, the element em0_2 links to a node with three elements at the level 1: “AMERICA”, “BANK” and “COMMERCIAL”. The element “AMERICA” links to another node at the level 2 and so on, at the level 7, the element “101010” is at the leaf level and contains [{Merlu, 1024}, {Abba, 392}] (list of {FID, CID} has two elements).

Basing on this CN Tree, the search engine can find all {FID, CID} of a requested "company name". For instance, if the query is “ABC CAPITAL GROUP” then the result is {“Skada”, “B123”}, etc. Indeed, this index also supports an approximate search i.e. users might not know the sufficient name of a company so they just input its first few worlds, e.g. the query is “ABC CAPITAL” then the result list will be {“Skada”, “B123”} and {“Abba”, “566”}. Next, we can retrieve all details of customers whose {“FID”, “CID”} are in the result list.

<table>
<thead>
<tr>
<th>Items (words)</th>
<th>List of {Fund ID, Customer ID}</th>
</tr>
</thead>
<tbody>
<tr>
<td>……</td>
<td>……</td>
</tr>
<tr>
<td>John</td>
<td>{“Abba”, “1234”}, {“Merlu”, “112”}</td>
</tr>
<tr>
<td>……</td>
<td>……</td>
</tr>
<tr>
<td>Murphy</td>
<td>{“Merlu”, “112”}</td>
</tr>
<tr>
<td>……</td>
<td>……</td>
</tr>
<tr>
<td>Smith</td>
<td>{“Abba”, “1234”}</td>
</tr>
<tr>
<td>……</td>
<td>……</td>
</tr>
</tbody>
</table>

Figure 3. An example of Customer Name Index

3.2.2. “Customer Name Index” is an index table based on inverted list technique. This index table consists of two parts: items and a collection of lists, one list per item (Figure 3). An item is a word from the “Customer Name” i.e. each customer name in BEP’s customer datasets is parsed in a set of separate words. For instance, the customer name “John Smith” is split into two words: “John” and “Smith”. A list L_w of a word w_i records tuples of {FID, CID} of customers whose names contain the word w_i. We have, for example, the customer “John Smith” with {FID= “ABBA”, CID= “1234”} and “Murphy John” with {FID= “MERLU”, CID= “112”}. Hence, the index table has three elements: [“John”: {“ABBA”, “1234”}, {“MERLU”, “112”}], [“Murphy”: {“MERLU”, “112”}] and [“Smith”: {“ABBA”, “1234”}].

3.2.3. “Address Index” is also an index table based on inverted list technique. Similarity to the “Customer
Name Index”, its index table consists of two parts: items and a collection of lists, one list per item (Figure 4). An item is a word from the “Address” i.e. each address in BEP’s customer datasets is also parsed in a set of separate words. For instance, we have an “address index” table as shown in Figure 4.

<table>
<thead>
<tr>
<th>Items (words)</th>
<th>List of {Fund ID, Customer ID}</th>
</tr>
</thead>
<tbody>
<tr>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>123</td>
<td>{“Abba”, “1234”}, {“Skada”, “347”}</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>Avenue</td>
<td>{“Merlu”, “112”}</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>Sunset</td>
<td>{“Abba”, “1234”}</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
</tr>
</tbody>
</table>

Figure 4. An example of Address Index

The whole index structure is shown in the Figure 5. In order to limit the search space, these datasets are also grouped by country (the most popular data field, ref. section 3.1). Basing on this organization, our search engine allows users to launch requests on customer information managed in different databases only through his name and address. If a customer is a corporate then the searching process will scan the CN Tree and Address Index table. Meanwhile, Customer Index Table and Address Table are used for an individual customer. Advantages and problems of this approach will be discussed in the section 5.

4. Implementation

We develop our approach as a search tool basing on distributed paradigm and this tool is implemented as web services that can support 2-tier or 3-tier application model (Figure 6).

We implement services for two kinds of users: end-users and administrative users. There are indexing, updating services for administrators. End-users exploit this system through searching and extracting services.

![Figure 6. Application models](image)

4.1. Indexing service

This service scans all 16 BEP’s databases one time and builds indexes of “Company Name”, “Customer Name” and “Address”. Elements in each node of “Company Name” index as well as items in “Customer Name” and “Address” index table are sorted by lexical order. Indexing service builds also a country list and each element in this list stores information (hash code) about appropriate entries of three indexes above. These indexes are organized is main memory and this service allows also to save them in secondary memory. Hence, administrator only needs to create indexes one time and stores them in databases (index databases) and then each time she/he reloads it to main memory at the launching of the application. In the real world of banking application, these indexes are loaded permanently in the main memory of servers and are synchronized time by time with their databases (index databases) automatically. The customer information is not real time data processing i.e. when a customer opens an account, he always wait a period of time for security checking (1 day, for example) before it is activated to perform his first transaction. Therefore, if indexes in the main memory are damaged by the
system halt, the electric cut, etc., administrators can reload them from index databases without losing information.

4.2. Updating service

When indexes are being exploited, new customer profiles are added in BEP’s customer datasets. Therefore, this service allows updating new customer information into indexes. It updates firstly in the main memory of servers and it then synchronizes this information to index databases. The update service is automatically performed at every mid-night by scanning 16 BEP's databases to detect update information (every update information of customer are always stored for auditing).

4.3. Searching and extracting service

A searching request submitted by end-users includes customer/company name and its address. Searching service bases on this information to look for a set of related {CID, FID} on “Company Name”/ “Address” indexes (corporate customer) or on “Customer Name”/“Address” (individual customer). Basing on the result set, queries will be performed on BEP’s databases to retrieve related customer information. Users can choose which information needed to extract or to perform more investigations.

5. Evaluation and discussion

5.1. Experiments

We implement and test our approach on a simulation platform with BEP’s customer datasets. The database architecture is similar to BEP’s databases which are being exploited. The simulate material platform for testing includes 1 Pentium Dual Core 3.4Ghz 2Gb RAM Windows Server 2003 (data server), 1 Pentium 4 Hyper Threading 3.4Ghz 1Gb Windows XP SP2 (application server), 1 Pentium 4 2.7Ghz Windows XP SP2 512Mb (front-end user). This web service-based tool is developed by C#/Visual Studio 2005 and DBMS used is SQL Server 2005. All services are implemented at the application server and datasets are managed by data server (3-tier model). The number of records is about 32000 for all 16 databases.

We launched different tests on this platform and take the average results. The indexing time \( I \) is \( \sim 17 \) seconds. The total searching time \( S \) is \( \sim 15 \) seconds (15s 40ms) for one request. The searching time \( S \) is composed of local searching on our indexes, query process by SQL server and communication overhead; among them the local searching only takes \( \sim 2 \) milliseconds on the application server. We launch also a customer search by SQL queries with exact “customer/company name” and “address” automatically on 16 databases to compare with our approach and it takes \( \sim 3 \) minutes for one request.

5.2. Discussion

Our approach presented in this paper has many advantages. First of all, it solves the problem of 16 independent and separate databases by providing a global view of all customer information without changing the current architecture of BEP’s databases system. Then, this approach also overcomes the data quality problems that normally take an important time to improve, especially the manual correction of incoherent address data. The preliminary tests show that it is efficient. It gains \( \sim 10 \) times faster than normal approach by DBMS queries (automatically running) and gains more further then the manual approach. Moreover, our approach also supports for parallel processing where two threads can be launched to search independently on “Company/Customer Name” index and “Address” index. It can benefit the multi-core architecture of BEP’s servers.

There are two main aspects of this approach that need to be improved. The first one is memory consumed because all index structures are stored in the main memory. However, each item stored is not a word but its hash code and it takes a small amount of memory by experiments. Furthermore, in the real BEP’s servers, main memory size is greater than 100 Gb and whole indexes take less than 0.2%. Besides, loading index in the main memory is normal approach of many current DBMSs to exploit it efficiently. Another aspect is the replicated of items in “Company Name” tree, e.g. the word “BANK” exists in many nodes (Figure 2). This problem can be improved by replacing this tree with a graph where each item appears one time as a node and edges represent for paths linking these items.

6. Conclusions and Future Works

In this paper, we presented an approach for identifying customers registered in an investment bank. This approach has been developed as a tool which is a set of web services on a distributed platform. The contribution of this research is to provide a set of indexes combined from suffix-tree based and inverted list in order to overcome the problem of database design and data quality of BEP’s customer datasets.
Throughout preliminary estimations of each service and its performance on a simulation platform with BEP’s datasets, we can conclude that our customer search is an efficient tool and it satisfies the needs of banking users in their AML tasks. Experimental results on real-platforms of BEP are also being produced and allow us to test and evaluate the tool robustness. We are currently working on the graph index approach that takes in account the memory consumed problem to tackle with huge datasets. A multithreading version is also being developed and tested.

References


