CS4224D FINAL REPORT

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# Team member contributions

## Chen Xing

* Citus data modelling / import
* Main driver program
* Slurm shell for benchmarking

## Chin Wee Nie

* Preparation of all setup scripts and slurm related scripts
* Data modelling and functions for transaction 2, 4, and 7
* Preparation of README for the whole benchmarking flow
* Setup and deploy Cassandra benchmarking run using different configurations

## Jan Alfenson Tan

* Install, configuration and maintenance of Cassandra on compute nodes
* Data modelling and functions for transactions 3 and 8
* Debugging and testing of transactions
* Reorganization of Cassandra transactions to improve transaction isolation
* Compilation of Final Report

## Liu Jiahui

* Data modelling and functions for transactions 1, 5 and 6
* Preparation of client.csv, throughput.csv and dbstate.csv

## Liu Keyi

* Citus data modelling / import
* Main driver program
* Slurm shell for benchmarking

# Cassandra implementation

## Description of data models

**Undelivered orders by warehouse district**

To support transaction 2.3 “Deliver Transaction”, we decided to model a table that holds the ‘warehouse id’, ‘district id’, ‘order id’, ‘customer id’ and ‘carrier id’ fields. It is partitioned by w\_id and d\_id, with clustering order on o\_id. It is quite similar to the orders table, except it has some additional features to support the transaction.

First, the undelivered orders table contains only undelivered orders, where carrier\_id = null. This allows us to quickly get any undelivered orders without searching through existing delivered orders.

Secondly, an ascending clustering order on o\_id allows us to select for the oldest order quickly given a w\_id and d\_id, as the oldest undelivered order is denoted to be the undelivered order that has the smallest order number of all undelivered orders. As such, a simple select statement with a w\_id, d\_id LIMIT 1 will allow us to get the oldest undelivered order.

Although this approach runs into a rather unavoidable problem. In the transaction, once we process an undelivered order, as the order become delivered, we delete it from the undelivered orders table. However, this leads to many deletes on the table. This leads to the problem where Cassandra looks through the tombstones of many deleted rows before it can reach the first row which is an undelivered order, causing the runtime of the search for a undelivered order to be much higher than simply getting the first row in a partition. This is knows as the queue anti pattern in cassandra tables. However, due to the nature of the transaction, this is an unavoidable problem, and this reflects on some of the limitations of using a sstable based database.

One way we reduce this problem of tombstones building up is by reducing the gc\_grace\_seconds property of the table to be 0. This allows cassandra to delete the tombstones created during compaction immediately, reducing the number of tombstones.

**Orders\_by\_customer**

On the other hand, order-status transactions utilize an extra denormalized table named orders\_by\_customer. The table consists of the following columns, C\_W\_ID, C\_D\_ID, C\_ID, O\_ID, O\_CARRIER\_ID as well as O\_ENTRY\_D. The table has a composite primary key with the combination of C\_W\_ID, C\_D\_ID, C\_ID, and a clustering column of O\_ID in descending manner. Unlike the first and second data models proposed for the top balances transaction, the "orders\_by\_customer" table is designed to be more resilient to updates, particularly with regards to the O\_CARRIER\_ID value originating from the new-order transaction and delivery transaction. While new-order transactions necessitate the insertion of new rows into the table, deletions are not a concern. This robustness arises from the fact that O\_CARRIER\_ID neither serves as a primary key nor functions as a clustering column. Consequently, it is eligible for modification through straightforward update statements.

​​This presents a notable contrast to the top-balances table discussed earlier. While materialized views offer several advantages, they entail trade-offs that might not align optimally with this specific scenario. For instance, we anticipate that 40% of the workload will originate from the new-order transaction, responsible for creating new records in the table. Meanwhile, there is another 20% of the workload stems from the delivery transaction, contributing to updates of the O\_CARRIER\_ID value. Given this substantial workload, materialized views may not be the most suitable option here. While they excel at enhancing read performance by precomputing and optimizing data for specific query patterns, they may not be well-suited for scenarios characterized by frequent updates to non-primary key columns. Such updates can trigger the regeneration of the entire materialized view, introducing potential inefficiencies.

Hence, in this context, opting for an additional denormalized table proves more efficient. It is tailored for write-intensive workloads with high update rates, allowing direct updates to the denormalized table without affecting other views or tables. We think that the minor overhead associated with maintaining and synchronizing data across distinct tables is justifiable, given the substantial benefits it offers for handling write-intensive transactions.

**Popular\_item\_transaction**

For this transaction, we attempt two data models. One of them is generating a denormalized table by combining order\_line table and stocks table with join; the other one is utilizing the original tables.

The new table consists of columns: W\_ID, D\_ID, OL\_O\_ID, OL\_NUMBER, I\_ID, and S\_QUANTITY, with W\_ID and D\_ID as partition keys, OL\_O\_ID and OL\_NUMBER as clustering columns, within which OL\_O\_ID column is sorted in descending order. The reason of conducting a denormalized table is intuitive: the results can be retrieved with one query. However, this data model achieves high reading efficiency in trade of huge overhead in update. We need to take transaction one into consideration, where new orders and order lines are created. When new orders are placed, stocks must be updated accordingly. While it is easy to update stock table with primary key W\_ID and I\_ID, it is not the same for the new table. Recall that the new table have W\_ID, D\_ID, OL\_O\_ID and OL\_NUMBER as primary keys. To update it, we need a list of order lines that are from specific warehouses and have corresponding items. This requirement induces a need of another new table, whose maintenance would bring up new issues.

In this scenario, we choose to use the two original tables directly. Here we need to carefully design the data model for order line table and stock table. For the first one, its primary key is set as ((OL\_W\_ID, OL\_D\_ID), OL\_O\_ID, OL\_NUMBER). OL\_O\_ID is put in cluster columns but not partition columns for the reasons: 1. order number is highly diverse compared to W\_ID and D\_ID; 2. We need to perform range query on OL\_O\_ID. For the stock table, its primary key is set as ((S\_W\_ID), S\_I\_ID) with S\_I\_ID in ascending order. Despite we want to perform range partition on S\_QUANTITY, it is not in primary key because it is frequently updated by transaction 1.

**Top\_balances**

To determine the top 10 customers with the highest c\_balance values for top-balance transactions, we explore several data modeling approaches.

The initial model involves the creation of a new table, "top\_balances," which includes columns for C\_BALANCE, C\_ID, C\_NAME, C\_W\_ID, W\_NAME, D\_NAME, C\_D\_ID, and DUMMY\_PARTITION\_KEY. All records in this table share the same value for the partitioning column, DUMMY\_PARTITION\_KEY. Within this setup, the records are sorted based on the C\_BALANCE column in ascending order. We employ the LeveledCompactionStrategy for compaction management. However, this model has limitations as it necessitates a single partition to store all the data. It may be suitable if the partition is expected to contain a relatively small, fixed number of records, but in real-world scenarios where customer bases tend to expand, this approach becomes less practical.

The second data model employs the same "top\_balances" table but differs in its choice of partition key, using C\_W\_ID instead. Each partition includes records ordered by three clustering columns: C\_BALANCE (in descending order), C\_D\_ID, and C\_ID (in ascending order). Given the use of C\_BALANCE as a clustering column, updates to C\_BALANCE values are not supported. Consequently, insertions and deletions are used whenever C\_BALANCE values need to be updated.

The third data model, which is the data model we opt for the “top\_balances” table, leverages a Cassandra Materialized View table derived from the customer base table. In contrast to the first and second models, which create new denormalized tables, a materialized table eliminates the need for manual synchronization of C\_BALANCE values between multiple tables. Moreover, opting for an extra denormalized table in the first and second models introduces certain complexities. Specifically, when using C\_BALANCE as the clustering column, precise matching of C\_BALANCE values in the WHERE clause of deletion transactions becomes critical for proper execution. This can potentially pose challenges, particularly for columns like C\_BALANCE that store decimal or float data types. To mitigate this, additional logic must be implemented to round decimal places before updating the new C\_BALANCE value in the extra denormalized table.

In summary, the use of materialized views not only simplifies development but also significantly reduces the risk of synchronization errors. It offers a more efficient and elegant solution for maintaining data consistency and optimizing network traffic, making it a compelling choice in scenarios like this.

**Orders by warehouse district customer**

To support transaction 2.8, “Related customers”, we decided to model a table that holds the ‘warehouse\_id’, ‘district\_id’, ‘customer\_id’, ‘order\_id’, ‘orderline\_number’ and ‘item\_id’. It is partitioned on w\_id, d\_id and c\_id and are clustered on o\_id and ol\_number. This table is essentially a join between the orders table and the orderline table. As such the primary key has to hold w\_id, d\_id, o\_id and ol\_number. c\_id was an additional field added to the partition key to support the transaction, which we will elaborate on below.

c\_id was added to the partition key to support looking for rows given a customer identifier. For txn 2.8, we are given a customer identifier (w\_id, d\_id, c\_id), and are supposed to look for any other customer that does not share the same w\_id, and has ordered 2 of the same items. As such, we can select for the customer given the customer identifier from this table as it is partitioned on these fields.

A secondary index on item\_index was also added to this table. This is to support selecting for rows given a item\_index. Part of the implementation of this transaction involves looking for related customers using the ‘i\_id’ of the items bought by the given customer. This secondary index allows for such a query without looking through every partition.

To support this transaction, we initially considered pre-computing tables with 2 different items in the same order on the same row. However, after some initial testing generating these tables, we found it was unviable. As the orderlines table has more than 3 million lines, precomputing such a table can potentially create 3m^2 rows, which is way too much storage required for a table. Thus we decided store the table this way, and do post-processing to generate the results for the related customer’s transactions

## Implementation of transaction functions

**New Order Transaction**

The function of transaction one is placing new orders. New orders are identified by O\_ID, thus we need to ensure that O\_ID is unique and new data would not be overwritten when multiple clients are creating new orders. To achieve that, strong consistency level is necessary when updating last order number in district table and inserting new data into order table. When the overall consistency level of database is “ONE”, the consistency level of “last order num update statement” and create order statement are set to “ALL”. Thereby last order number look up statement and order table acquire strong consistency with “Read-One-Write-All” protocol. Notice that this additional setting is omittable when the overall consistency level is Quorum, because all reads and writes would be under strong consistency in such environment. In this case, clients on all nodes will receive the latest and consistent order number, so that we can reduce the probability of multiple attempts on creating new order. The option “IF NOT EXISTS” in create order statement indicates conditional update, which has default consistency level of serial. With such settings, in the case of multiple concurrent insertions, only one request would be executed.

The execution of the queries are put into a while loop to make sure the transaction is secure. Since the queries might be run multiple times, they are put into prepared statement to improve efficiency. Prepared statements will be parsed and saved in Cassandra and therefore lowering network traffic and CPU utilization.

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After inserting order data, we need to insert corresponding order line data and update related tables. We apply batch statement on item-, or orderline-, level, to ensure atomicity and availability. Batching on order level would result in higher latency and low availability, because the whole transaction will fail if one of the statements fail to execute. Likewise, the statements are prepared outside of for loop.

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Other relevant tables are updated in asynchronous manner, so that the queries could be executed concurrently to improve throughputs.

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**Payment Transaction**

To compute the new C\_BALANCE, we first query the customer using the supplied C\_W\_ID, C\_D\_ID and C\_ID with a prepared statement, we then decrement this old balance value by the payment. Similarly, we query the specific warehouse and district before incrementing the W\_YTD and D\_YTD values respectively. Once the calculations are done, we convert cast new value back to Decimal to ensure the data type consistency. To ensure the atomicity of the update transactions, we wrap the 3 statements using a BatchStatement function supplied by the Cassandra driver for its atomicity and isolation guarantees. If any statement within the batch fails, none of the changes in the batch are applied to the database, ensuring that either all statements in the batch succeed or none of them do.

With a replica factor of 3, using quorum helps ensure that at least 2 nodes agree and acknowledge the writes as successful. This offers a good balance between availability and consistency for our case.

A computer screen shot of a program

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**Delivery transaction**

For delivery transaction, we select from the undelivered orders table the first row from every district given a w\_id from d\_id 1 - 11. As the table is partitioned on w\_id and d\_id, this selection is efficient. The ascending clustering order of o\_id also ensures the first row from the partition is guaranteed to be the oldest undelivered order.



With this select, we have all the other information required to update the other tables, namely ‘w\_id’, ‘d\_id’, ‘o\_id’, and ‘c\_id’. These values encompass the partition keys on the other tables we need to update, which in turn ensure efficient updates.

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Finally, we delete the delivered orders from the undelivered orders table. This is also efficient as we have ‘w\_id’, ‘d\_id’ and ‘o\_id’, which makes up the primary key of the undelivered orders table.

**Order Status Transaction**

As the orders\_by\_customer table already maintains each customer's orders in descending order, obtaining the most recent order status for a given combination of C\_W\_ID, C\_D\_ID, and C\_ID becomes a straightforward task. It simply involves the execution of a simple statement, as demonstrated below:A computer screen with text

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Similarly to display the order items belonging to the last order, we use another simple statement as followed:

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**Stock-level Transaction**

The implementation of this transaction requires three query statements. First, we request the latest order number from district table with W\_ID and D\_ID. Then, we fetch a list of items from the last L orders of the specific warehouse and district. The duplicate entries are removed from item list on client side, because “distinct” operation can only be applied on primary key. After that, we search the stock quantity for all the items. One might argue that using IN relation is bad in Cassandra. However in this case S\_I\_ID is not one of the partition key, and partition is selected based on S\_W\_ID. Thus no matter how we query the stock table, with IN relation or one by one, we are reading only 1 partition, so the performances of two approach are the same. Finally, we count the number of item whose stock quantity is below threshold. Filtering is done on client side because S\_QUANTITY is not one of the primary keys, and filtering S\_QUANTITY would cause unpredictable performance inside Cassandra.

电脑屏幕截图

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The implementation of transaction 5 only consists of read operations. From the requirement of this transaction, we decide that it can tolerate stale data and therefore strong level consistency is unnecessary. The consistency level of all three read operations are fall back to default “ONE”.

**Popular-Item Transaction**

The implementation of this transaction requires two query statements. First, we request the latest order number from district table with W\_ID and D\_ID. Second, we search for the required info in new table. Finally, the percentage of orders that contain the item is calculated on client side.

Our implementation is efficient because most of the information can be gained with one query from Cassandra database. Since W\_ID and D\_ID is deterministic, we only need to look at one partition. Within the partition, the filtering on O\_ID is still fast because O\_ID is sorted in table. After we obtain the data from database, we choose to calculate the percentage with NumPy for its efficiency and simplicity.

手机屏幕截图

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From the requirement of this transaction, stale data seems acceptable and therefore the consistency level of all three read operations are fall back to default “ONE”.

**Top-balances transaction**

By leveraging the top\_balances table as a materialized view of the underlying customers table, we streamline the process of retrieving the top 10 customers with the highest C\_BALANCE within each partition. Initially, we retrieve a list of 100 records across the 10 partitions of top\_balances table, subsequently followed by a sorting operation at the application layer to identify the absolute top 10 records becomes highly efficient. In this scenario, sorting a fixed amount of data can be viewed with a time complexity of O(1), signifying minimal computational overhead. It is worth noting that we perform the 10 distinct queries on the materialized view table, each involving a different warehouse ID. However, the use of prepared statements significantly aids in optimizing these queries, by eliminating the need to reparse and reoptimize the query for every execution, saving CPU and memory resources.A screen shot of a computer

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**Related customers**

For related customers, we initially find all the orderlines from orders made by a customer using w\_id, d\_id and c\_id. This is fast as the orders\_by\_customer table has those fields as the partition key. Then, we generate a table with 2 unique items per row by doing an inner join on ‘w\_id’, ‘d\_id’, ‘c\_id’ and ‘o\_id’ between 2 copies of the result table, then filtering any rows with 2 same ‘i\_id’. This resulting table contains every combination of 2 unique items per row, where both items are purchased in the same order by the same customer.

We then get all the unique i\_id from the above orderlines and select for all orderlines with this i\_id. This is efficient as well, and does not require looking through all partitions, as we create a secondary index on i\_id for the table. We then remove all rows with the same w\_id as the customer, then perform the same inner join and filter as above to generate a table with 2 unique items per row.

Finally, we perform a inner join between both tables on the 2 items. Thus, the matching rows from the second table indicate that customer has made a purchase with 2 same items as the given customer. We take customer identifiers from the second table, filter duplicates from there, and return them as the result of the query

**Essential configurations**

In the configuration of Cassandra, we found that most of the default values provided were sufficient for the project. As such, only a few fields were changed in our configuration.

**seeds**

For our cluster, we designated 3 nodes to be the seeds. Seed nodes are used to bootstrap the gossip process for new nodes joining into the cluster. We initially were able to set the cluster up with 1 only. However, after a patch in week 12, we found it was necessary to have 3 seed nodes running for the non-seed nodes to be able to join the cluster.

**listen address**

The listen address of the nodes is set to be the private ip address of the nodes in the HPC cluster. E.g.(192.168.48.249). This is changed from the default value (localhost) as we need the nodes to be able to communicate with other nodes within the cluster. As all node are within the same internal nus soc network, a private ip address is sufficient for communication.

**broadcast address**

We left this blank, which Cassandra will take the listen address’s value by default.

**rpc address**

We set this as the private ip address of the node as well. This is the ip address used by clients running on the node to connect to Cassandra.

**read/range\_timeout\_values**

We set this value to 300000ms as we found the queries involving collating the dbstate statistics required a large amount of time.

**endpoint\_snitch**

GossipingPropertyFileSnitch was used for the cluster. From research done on this parameter, we found that it was the preferred snitch for production use.

**Performance benchmarking**

To facilitate benchmarking and assess the impact of various consistency levels, we employ two distinct sets of consistency strategies on two different setups of data models. In the first set of benchmarks, the QUORUM consistency level is uniformly applied to all transactions, encompassing both write and read operations. In the second benchmarking set, we adopt a more flexible approach, applying the QUORUM and ALL consistency level selectively to transactions based on the specific importance of data consistency. Notably, in the second benchmarking set, we consistently utilize a ONE consistency level for all read transactions, ensuring swift access to data while adjusting consistency for write operations to suit the requirements of data integrity in each case. The two sets of consistency level are applied to the data models with Materialized views, and the data models without Materialized views for comparison. The results are tabulated as followed:

Table 1 Consistency benchmarking with Materialized views

|  |  |  |  |
| --- | --- | --- | --- |
| Consistency level | Min Throughput | Max Throughput | Average Throughput |
| QUORUM | 7.66 | 31.16 | 13.46 |
| Selective QUORUM and ONE for reads | 7.89 | 31.89 | 13.59 |

Table 2 Consistency level benchamrking without Materialized views

|  |  |  |  |
| --- | --- | --- | --- |
| Consistency level | Min Throughput | Max Throughput | Average Throughput |
| QUORUM | 6.49 | 24.64 | 10.59 |
| Selective QUORUM and ONE for reads | 6.40 | 24.43 | 11.03 |

By analyzing the distinctions in the results obtained from two different benchmarking runs (Refer to table 1), we manage to gain some insights into the performance characteristics and trade-offs in Cassandra when different parts of CAP theorem are prioritized.

The most distinction between the two benchmarking runs is the impact of consistency levels on throughput. In the first run, where the Quorum consistency level is applied uniformly across all transactions, the latency tends to be higher. This is because Quorum requires more acknowledgments from replicas before considering a transaction as successful. As a result, write operations in particular can experience higher latencies due to the need for coordination among multiple replicas, leading to smaller overall throughput. In contrast, the second run, which selectively uses Quorum for writes, demonstrates smaller latencies. This indicates that for some write transactions, using a lower consistency level (such as ONE) can lead to quicker data writes, but with a potential trade-off in data consistency as some replicas may not receive the write or may have outdated data. This trade-off highlights the need for careful consideration of the specific data model and application requirements. It suggests that, in certain scenarios where strong consistency is not critical, adopting a more relaxed consistency level for some writes can lead to improved performance. Nevertheless, the results do not show a very significant distinction in terms of throughput. This could be due to us keeping some write to be ALL, in order to maintain strong consistency in essential transactions like new\_order. Other potential factors that could be tuned for further exploration include different indexing, compaction strategies and transaction function implementations by using read ahead caching. Since Cassandra utilizes bloom filters to check for the existence of data in a partition, we could potentially tune the size of filter and number of has functions to improve read latencies.

Throughput variation is notable when altering data models. Specifically, data models utilizing Materialized Views have been observed to enhance average throughput, achieving around 13 transactions per second at consistent consistency levels. In contrast, data models that depend on manual insertions and deletions within the denormalized 'top\_balances' table yield lower throughputs, with an average near 10 transactions per second. This reduction is partly due to the increased duration of lock contention by batch statements, which aim to preserve atomicity during updates to the customers base table and the 'top\_balances' table. Such operations can impair both read and write performances. Given that modifications to the C\_BALANCE value result from payment and delivery transactions—accounting for up to 40% of the workload—the performance impact of batch operations is substantial.

While Materialized Views offer several advantages, their implementation in production environments is not advised, due to its experimental nature. Furthermore, there are certain limitations to its usage. For example, no current solutions rectify data inconsistencies between the base table and Materialized Views; thus, a consistency level stronger than ONE is advisable. Repairs should be conducted on both base tables and associated Views, especially after reassignment of Cassandra nodes, to avert data loss. It is worth noting that even though Materialized Views eliminate the need for manual deletions during column updates within the Views, the generation of tombstones persists behind the scenes. Therefore, it is wise to carry out repairs regularly to maintain system health.

In conclusion, these benchmarking results provide valuable insights for real-world applications. They highlight the need to balance data consistency and performance requirements based on specific use cases. It also emphasizes the need for thorough testing and profiling to identify the optimal consistency levels and data models for different parts of the application. Ultimately, the choice between strong consistency and low latency depends on the application's criticality and the tolerance for data staleness.

# Citus implementation

## Description of data models

We named all tables with plural form of the names given in the project.pdf, because the phrase “order” in SQL is interpreted as other usage, leading to compile error if directly used in creating tables. Thus, the order table “orders”, and made this naming convention consistent along all tables.

For the first 2 tables(warehouses, districts), we created them as reference table, They are replicated on each worker node and can be used directly without cross-node communication when executing queries. We did this to reduce communication cost because they are small tables, do not change between transactions and are frequently used in many transactions.

A screen shot of a computer program

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When it comes to customer and order table, we followed the data schema provided in the project pdf. We distributed them based on column ‘warehouse id’. This selection of distributed key is comprehensible because w\_id is a common column shared among most tables (foreign key constraints between distributed tables require the tables distributed on the same column) and A computer screen with colorful text

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For the items table, unlike other 6 tables, it doesn’t have warehouse id, which means it cannot be distributed to nodes(because of foreign key constraints related to order lines and stocks), so we modelled it as reference table.

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For the last 2 tables(order\_lines and stocks), we distribute the two tables on warehouse id first, and then use alter phrase to establish two foreign key constraints on each table respectively according to the project requirements.

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We defined all foreign key constraints out of the brackets of create table phrase(as images showed below), as we encountered an error related to foreign keys between local table and reference table, which made us realize that PostgreSQL considers a table as a “local table” before the create\_distributed\_table function is executed(within the brackets), and it will be converted back to postgres tables as it is not chained with reference table. This citus related conversion will lead to a loss of relation and system error.

We created 4 indexes to facilitate transaction query as below, because the table districts, warehouses and items will not change in transactions, these index will not affect running of insertion and update. Besides, d\_w\_id, d\_id, w\_id and i\_id, these 4 columns are frequently used in ‘where’ and ‘join’ condition, so to create indexes for them improves the transaction efficiency.

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For the ALL\_LOCAL attribute of order line, instead of using a trigger(we failed to add a trigger for insertion under such a distributed environment), we implement the logic of comparation and judgement in our New-Order transaction level.

## Implementation of transaction functions

**Overall Structure**

~/citus\_code

main\_driver.py

./transactions

python functions for completing transactions

./preparation

sql for delete tables, data modeling and data importing

./data\_files

txt of source data for 7 tables

./result

csv files of running result

./xact\_files

txt of client operation

The main\_driver.py is considered as the main program of the project, which imports transaction functions from folder ./transactions. It uses sys.stdin to read txt from ./xact\_files, then uses conditional phrase to identify transaction\_type and calls corresponding transaction function. Latency related statistics are written into csv stored into result file.

**New Order**

**Brief Description:** This transaction receives a new order and update tables of districts, orders, stocks, and order\_lines.

**Processing Steps:**

1. Get the next order number for the district (get d\_tax at the same time for final amount calcualtion later):

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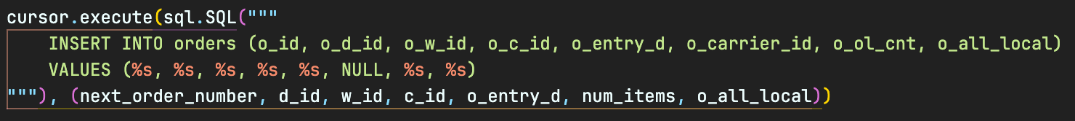
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1. Increment the D\_NEXT\_O\_ID for the district:

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Description automatically generated

1. Create a new order with order details:



1. Process each ordered item and update stock information:

A screen shot of a computer

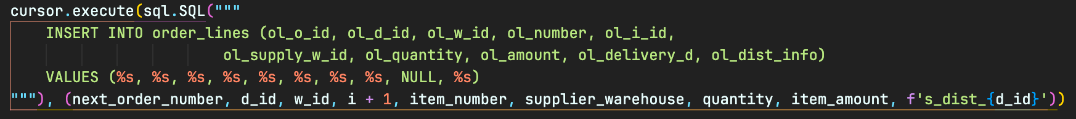
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1. Calculate item amount and update total amount:

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1. Create a new order-line for each item:



1. Get tax rate of from districts, warehouses and customers table, and calculate final amount:

A screen shot of a computer program

Description automatically generated

**Efficiency Consideration:**

1. From my implementation, I tried to minimize db accesses. For example, when calculating the final amount, I queried for customer details as well for later use to print out customer information without accessing the db once more.
2. Reducing complexity to database, move calculation logic to the code. Instead of aggregating total amount in the database, I save intermediate results and do the calcualtion in the code, saving processing time.
3. The total processing time of this transaction is about 100ms, which is acceptable.

**Payment**

**Brief Description:** This transaction takes in a payment amount along with the customer identifier (C\_W\_ID, C\_D\_ID, C\_ID), updates year-to-date payment for the warehouse and the district, also updates the customer’s balance, year-to-date payment, and payment count. Outputs customer, warehouse, and district information along with the payment amount.

**Processing Steps:**

1. Update year-to-date payment for the warehouse

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1. Update year-to-date payment for the district

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1. Update customer’s balance, year-to-date payment, and payment count

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1. Retrieving details of customer, district and warehouse

A screenshot of a computer program

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**Efficiency Consideration:**

1. The first 3 steps updates on warehouses, districts and customers table, where these tables are partitioned by warehouse id, hence we know which parition to update, and only one server will be accessed, reducing the I/O cost of accessing multiple servers.
2. The last step combines three queries into one, instead of query 3 times, we join the information retrieved from warehouses, districts and customers table, cutting down the I/O cost.

Moreover, since the three tables are all partitioned by the key of warehouse id, there’s no communication cost in between the servers, as all data resides in one server, so that the joins are performed locally.

**Delivery**

**Brief:** This transaction is used to process the delivery of the oldest yet-to-be-delivered order for each of the 10 districts in a specified warehouse.

Following the processing steps in the project file, a loop is start to traverse all district No.1 to No.10 :

* Step1. Use ‘select min(o\_id) from orders’ to find the smallest order\_id with no carrier allocated
* Step2. Update identifier of carrier who delivered the order to carrier\_id(input)
* Step3. Set data and time of delivery to now() in order\_lines table corresponding to the order

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* Step4. Update customer balance and delivery count, use subquery ‘select sum(ol\_amount) from order\_lines’ to increment balance, original count is added by 1

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Description automatically generated

**Efficiency consideration:**   
Redundant I/O is commented out all in code to improve the transaction’s running speed. Select and update queries are written as precisely as possible.

**Order Status**

**Brief:** This transaction queries the status of the last order of a customer.

Following the processing steps in the project file:

* Step1. Get customer information(name, balance) using customer identifier(input)
* Step2. Use ‘order by o\_id desc limit 1’ to query the last order info in orders table
* Step3. Search each item attributes in the obtained order from order\_lines table
* Step4. Print all customer-related information

**Efficiency consideration:**

Logic of this transaction is simple and there is not much space for optimization. I commented out all irrelevant debugging I/O in code to improve its running speed.

**Stock Level**

**Brief Description:** Given a warehouse id and district id, for the items from last L orders, this transaction counts the number of items with stock quantities below a given threshold and outputs the result.

**Processing Steps:**

1. Get the next available order number for a specific district.
2. Retrieve the set of items from the last L orders for a district.
3. Check the stock quantity for each item in the retrieved set against the threshold.

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Description automatically generated

**Efficiency Consideration:**

1. My first implementation was separating 3 steps, retrieving next avail order number N, followed by the set of items from the last L orders using N, then go through a loop to count how many items that its stock level is below the threshold. This may incur more I/O cost.
2. Since we partitioned order\_lines and stocks tables by the same key (w\_id), we are ensured to perform the join locally without incur more communication cost between servers. Hence this might be a better solution.

**Popular Item**

**Brief Description:** This transaction is to find popular items in the last L orders at a specified warehouse district.

**Processing Steps:**

1. Retrieve the next available order number for a district (N).

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1. Fetch the last L orders for the specified district (S) and related customer details.

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1. Retrieve order lines for orders in S.

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1. Process orders to find popular items.

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1. Calculate the percentage of orders containing popular items.

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**Efficiency Consideration:**

1. My initial implementation for step 4 was having a for loop to query on the order line to retrieve information, the total duration of executing each transaction can be as high as 15s to 20s, which is unacceptable and drastically lowing down the whole process. After further optimization, I stored the intermediate results in to a dictionary and output directly from the dictionary, this effectively cut down the execution duration to around 60ms to 70ms.

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1. We partitioned the tables by warehouse id, hence most of the join operations will be performed locally on a single server, this further cut down the communication cost.

**Top Balance**

**Brief:** This transaction finds the top-10 customers ranked in descending order of their outstanding balance payments.

Following the processing steps in the project file:

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**Efficiency consideration:**

Indexes on w\_id and d\_w\_id are set in data\_modeling phase to speed up match of join on and improve efficiency.

Use inner join to reduce the size of result set. The join order is warehouses >> districts >> customers, which is sort by table size in ascending order. To join small tables first reduces the row size of afterwards join operation, which improves transaction efficiency.

**Related Customer**

**Brief:** This transaction finds all the customers who are related to a specific customer with a different warehouse id. They have at least two items in common.

Following the description in the project file:

* Step1. Select candidate customers with different warehouse id, build a hashmap to map order\_line id to orders, traverse candidate customers
* Step2. For each candidate customer use set intersection calculation to get count of order\_lines match the requirement, if 2 order\_lines fit, the customer is related, which is to be added into answer
* Step3. Print related customer identifiers into answer set

**Efficiency consideration:**

In order to break down complex match requirements in this transaction and avoid massive join between orders and order lines, I implement loops, set and hashtable to complete the logic. This transaction takes a bit of more time to execute than the others. I am looking into using well-designed join at this time and this idea will be examined before the evaluation.

## Essential Configurations

**code path:**

~/citus\_code (shared by all nodes)

**sbatch config**(in go\_citus.sh):

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Description automatically generated**

**citus configs:**

database config:

user name: cs4224d

database name: citus\_project

port: localhost:5100

ip addresses for nodes:

xgpd3 192.168.51.42

xgpd4 192.168.51.43

xgpd5 192.168.51.44

xgpd6 192.168.51.45

xgpd7 192.168.51.46

**source route**(in .bashrc):

PYTHONPATH = ~/Python

**concurrency control level**: Read Committed(default of PostgreSQL, able to avoid dirty read)

**Performance Measurement**

sbatch start\_clients.sh to execute clients concurrently on slurm system

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Use

sacct -j <job\_id> --format=JobID,Start,End,Elapsed,REQCPUS,ALLOCTRES%30,Node

to monitor nodes running:

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Result of one node:

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**Reflections and Difficulties**

**Cassandra**

Slurm, while a powerful resource management system, can pose challenges, especially for newcomers. During the setup of Slurm batch jobs, we faced numerous issues related to CPU and memory allocation per task. These issues, though common, often resulted in misleading error messages that simply indicated unavailability of requested nodes without detailed explanations. Additionally, Slurm's documentation did not offer comprehensive guidance for effective debugging. As a consequence, a significant portion of our project time was allocated to resolving Slurm-related issues, diverting attention from our primary focus, which should have been centered on data modeling and analysis.

Through the project, we discovered the characteristics of working on a noSQL database. Unlike a relational database, there were many constraints placed on the types of queries supported to ensure performance. Therefore, data modelling required a top-down approach, with analysis starting from the query. We also had to consider the overhead of updating denormalized tables when modelling.

With the lack of join support, we had to do most of our transaction support either in the data modelling or post processing, by doing inner joins in our clients. For example, this was seen in the related customers transactions, and made implementing transactions more complicated that what a simple query in a relational database could do.

The lack of true updates in cassandra made for some difficulties in achieving high consistency in the distributed database. As cassandra does not allow updates of an existing row, to update a row in the table we had to do a read to get its current value, then write to the table again with the new row with new values. This has to be done in the client’s side, and created a latency which allowed updates from different clients to potentially interleave, leading to non isolated transactions. This meant we had to organize the transactions in our functions to reduce the latencies as much as possible.

The method Cassandra used to handle deletions was also a limiting factor, as accumulation of tombstones in a table meant longer look up times. This made the implementation of some transactions like the undelivered orders transactions difficult, as it required rows to be removed from the table each time a transaction was processed.

We found that the distributed nature of Cassandra allowed adjusting the consistency level to meet the requirements of the transaction and the use case. Through analyzing the requirements of the transaction, we could determine its consistency and availability to build secure and efficient application through hands on experience.

**Citus**

From the citus end, we originally used ssh to config nodes and test transactions on

xcnd30-34 manually. And many of our files were not stored below ~/.

Since last week, we could not access the nodes for 30-34 as permission was denied. Often, nodes were occupied by another user’s bash job.

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**Steps to solve:**

Firstly, we use ‘sinfo -t idle’ to search for idle which are available, Because the ssh method is banned, we used: salloc -p long -w targetnode  
srun --pty bash

to go to the coordinator and worker nodes:

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Then we finished installation and initialization on these new nodes following the Citus Documentation. We use cmd below to link to the database:

psql -U cs4224d -d citus\_project -h localhost -p 5100

During the process of adding nodes into citus system, we used ‘getent hosts xgpd3’ to get ip of the nodes, we set xgpd3 as coordinate node, and 4-7 as worker nodes.

* Add coordinator node:

SELECT citus\_set\_coordinator\_host('192.168.51.42', 5100);

* Add worker node:

SELECT \* from citus\_add\_node('192.168.51.43', 5100);

SELECT \* from citus\_add\_node('192.168.51.44', 5100);

SELECT \* from citus\_add\_node('192.168.51.45', 5100);

SELECT \* from citus\_add\_node('192.168.51.46', 5100);

Check citus nodes status:

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Finish data\_modeling and reimport:

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In order to prevent connection errors like below:

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We need to start pslq service on each citus node before we start transactions:

/home/stuproj/cs4224d/pgsql/bin/pg\_ctl -D /temp/teamd-data -l logfile start

Finally, we made our progress on database back and able to continue transaction concurrent test.

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