CLIENT-CENTRIC MOBILE OLAP

By

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Abstract

As the architecture for clients of a client-server OLAP system, the client-centric system distinguishes itself from other clients in the marketplace by incorporating a light-weight data engine, such that the client is capable of answering queries offline when the related data are cached in the memory. In a previous study of client-centric OLAP system, a web-based client is built. Three different data visualization scenarios have been identified for which the client can pre-load data into the client as a sub-cube from the server, so that the user may drill-down the sub-cube, with the help of the data engine. In this research, the app-based version of the client-centric OLAP is implemented. It runs on an android tablet featuring a multi-core CPU. From the comparative performance data, it is shown that the app-based client is superior to the web-based client in performance in most computational tasks of the three data visualization scenarios, especially when a parallel version of the app-based OLAP is deployed.

Keywords: Client-Centric OLAP; Mobile OLAP; Data Visualization; Parallel Computing

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1. INTRODUCTION

1.1 Platforms for OLAP Clients

In the marketplace, there is a large selection of OLAP (On-line Analytic Processing) client tools for the user to choose from. Traditionally, client tools run on a desktop connected to the server in a local area network. As web browsers became the user interface of choice, web-based client tools were introduced. Compared to desktop clients, a web-based client is more resource-constrained and consequently, performance and user experience suffer. On the other hand, it runs where internet access is available. There is also the benefit of user convenience, since there is nothing to install and maintain. The web-based client particularly appeals to casual users. In contrast, a desktop client nowadays can be as powerful as the machine the OLAP server runs on. It is capable of downloading a large dataset into its cache, and let the user analyze the data, and ask 'what if' questions, within his/her personal computing environment.

Over a last couple of years, a new application platform has emerged: mobile devices, e.g., smartphones and tablets. Smartphones and tablets are increasingly gaining popularity with the introduction of the iPhone, the iPad, and Google's Android. It is estimated that 59% of mobile phone users have smartphones by the third quarter of 2011 [4]. In addition, tablets are ready to replace the traditional personal computer [5]. Today, a smartphone or tablet is often the only computing device a person uses today. However, tablets such as the iPad are not only attractive to consumers, but also to business users. Tablets are helping doctors, lawyers, and businessmen to do their work [10, 11]. It is

1

estimated that the mobile office software market in North America may reach \$6.85 billion by the year 2015 [12].

Unfortunately, these mobile devices are constrained in memory size, CPU power, and network bandwidth compared to laptops and desktop computers. Because of the above constraints, the mobile web browsers of smartphones and tables are very slow in opening web pages due to slow resource loading [3]. In addition, the authors in [6] demonstrated that the JavaScript execution time is 20 to 80 times longer on smartphones than on desktop computers.

Vendors of OLAP clients on mobile devices differ in their product strategies [2]. Some vendors simply move their web-based systems that are built for desktops onto mobile devices. Others develop mobile applications that run on the native operating system of mobile devices, such as Android. The arguments in favor of native mobile applications can be summarized into three points: fast performance, superior user experience, and offline access. On the other hand, web-based OLAP has its own advantages in terms of portability and security. Some of the leading vendors, such as SAP Business Objects [13] and IBM Cognos [36] offer their client tools on all three platforms: desktop, web-browser and native mobile OS, e.g., Android from Google and iOS from Apple.

1.2 Client-Centric OLAP

In [27], Tim Hsiao developed a web-based OLAP prototype which incorporates a data engine for processing queries on the local data already downloaded from the server. He demonstrated the superiority of this approach by implementing three data visualization scenarios: top-K, moving average and scatter plot, where data may be pre-

2

loaded from the server. We will describe the first scenario to show how client-centric OLAP works.

Suppose a floor supervisor in an electronic store would like to get details about the top-k best sellers in the store in past few weeks in order to configure the floor display the next day. Usually, he would send a query to the server for top-k best sellers for a specific time, one at a time, by moving the slider on the user interface on his smartphone. With the data engine on the client side, a sub-cube with products and time dimensions can be downloaded to the client running on a browser for the drill-down and roll-up operations done entirely within the client. For this application, the user gets the same benefits due to offline data access, e.g., superior performance and enhanced user experience. To contrast these two approaches, we call them server-centric and clientcentric OLAP respectively.

However, there exists little research on client-centric OLAP clients for mobile devices. Other researchers study data cube construction and compression [1, 14, 15, 16] and query recommendation [17]. One major issue of client-centric OLAP is security. A large amount of important data stored on mobile devices is a concern for companies that value privacy and security, and it is difficult to enforce data consistency. Another important reason is that the data cube is likely to be too massive for previous generations of mobile devices to store in memory. Furthermore, downloading the data cube to the mobile device can be costly and time consuming.

1.3 Research Scope and Objectives

In this project, my focus is on client-centric mobile OLAP. In particular, I implement a client-centric OLAP prototype on a multi-core tablet running a version of

the Android operating system, hence an app-based client-centric mobile client. Being a client-centric system, this prototype is different from the mobile OLAP applications mentioned earlier because it contains a data engine for aggregation purposes. For comparison purpose, two versions of data engine are built: parallel and non-parallel versions.

The main objective of this project is to compare performance of the web-based OLAP, as described by Tim Hsiao, and the app-based client-centric OLAP. It is my hope that this study will increase the awareness of the client-centric OLAP systems in the OLAP industry. Should this type of Mobile OLAP system be of interest to a vendor, this study might help them to determine whether web-based or app-based system is more desirable for them.

Note that Tim's prototype has been significantly modified so that we can do an apple-to-apple comparison. In addition, Tim's prototype runs on a browser in a desktop system, and some of Tim's performance data are simulated. Thus this is the first time detailed experimental data are available for both web-based and app-based client-centric OLAP systems. Therefore, we include also the performance comparison with the server-centric OLAP system.

1.4 Organization of the Report

This report has five chapters in total. The next chapter provides a detailed description of the server-side components of OLAP system architectures. Afterwards, the implementation of the mobile clients is explained in chapter 3. Then chapter 4 discusses the performance evaluation of the client-centric and server-centric architectures. Finally, chapter 5 concludes this report and discusses possible future work.

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2. SERVER IMPLEMENTATION

OLAP systems have two architectures: client-centric and server centric. Figure 1 provides an overview of the client-centric architecture and figure 2 provides an overview of the server-centric architecture. There are four different components on the server-side. In this chapter, we explain each server-side component of both OLAP architectures.



Figure 1. Client-centric OLAP architecture



Figure 2. Server-centric OLAP architecture

2.1 OLAP Server

The foundation of any OLAP system is the OLAP cube. A cube is a set of numerical data categorized by multiple dimensions. This set of numerical data is the measures. For example, a two dimensional cube is a Cartesian product of the dimensions *A* and *B*, where *A* and *B* are both sets of items. Each element of the Cartesian product is assigned to a numerical value from a measure. When there are more than three dimensions, a cube is called a hypercube. A sub-cube is a subset of a cube. Figure 3 shows a three dimensional data cube with the dimensions Product, City, and Date.



Figure 3. A three dimensional data cube [21]

The OLAP server we use is Microsoft Analysis Services 2008 R2. The OLAP server retrieves a sub-cube from the OLAP cube by using Multidimensional Expressions (MDX) [18], a query language for OLAP databases. An example of an MDX query is shown in figure 4.

SELECT {[Customer].[Education].Children}ON 0, {[Customer].[Gender].Children} ON 1 FROM [Adventure Works]

WHERE [Measures].[Internet Sales Amount]

Figure 4. MDX query

This sub-cube is defined by two dimensions: [Customer].[Education] and

[Customer].[Gender]. The measure is Internet Sales Amount. The OLAP server processes this query and the result of this MDX query is displayed in table 1.

	Bachelors	Graduate Degree	High School	Partial College	Partial High School
Female	\$5,076,191.40	\$2,819,687.51	\$2,169,808.44	\$3,904,283.72	\$843,647.62
Male	\$4,823,951.36	\$2,640,872.75	\$2,468,217.63	\$3,819,259.17	\$792,757.64

Table 1. MDX query result

To allow application software to execute MDX queries, we use a standard protocol called XML for Analysis (abbreviated as XMLA).

2.2 ADOMD

ADOMD is a Microsoft .Net framework that implements the XML for Analysis (XMLA) protocol for communication with Microsoft Analysis Service. XMLA [19] is an Application Programming Interface (API) for data access in OLAP. It is based on XML, SOAP, and HTML. It allows an application to communicate with an OLAP server. XMLA has two methods [20]: Execute and Discover. The Execute message is used for sending query request to the OLAP server. The Execute request embeds an MDX query. The format of the result can be specified by the user. An example of an Execute request is shown in figure 5. The Discover request is used to retrieve information and metadata from the OLAP server. Like the Execute request, the format of the result of a Discover request can be also be specified by the user. Figure 6 shows an example that retrieves information about the cubes in an OLAP database. The results of both the Execute

message and the Discover message are highly detailed, containing information on

dimensions and axes.

<execute xmlns="urn:schemas-microsoft-com:xml-analysis"></execute>
<command/>
<statement></statement>
SELECT
{[Customer].[Education].Children}ON 0,
{[Customer].[Gender].Children} ON 1
FROM [Adventure Works]
where [Measures].[Internet Sales Amount]
<properties></properties>
<propertylist></propertylist>
<format>Multidimensional</format>
<axisformat>TupleFormat</axisformat>

Figure 5. XMLA Execute request

<discover xmlns="urn:schemas-microsoft-com:xml-analysis"></discover>
<requesttype>MDSCHEMA_CUBES</requesttype>
<restrictions></restrictions>
<restrictionlist></restrictionlist>
<catalog_name>Adventure Works DW 2008R2</catalog_name>
<properties></properties>
<propertylist></propertylist>
<catalog>Adventure Works DW 2008R2</catalog>
<format>Tabular</format>

Figure 6. XMLA Discover request

2.2.1 Metadata

Before retrieving the sub cube, the client first needs to request the SOAP web service for the metadata. The metadata contains a dimension's hierarchy. Figure 7 shows the hierarchy of the Gender dimension from the *Adventure Works* data cube. After selecting a dimension, detailed information on the dimension's hierarchy will be sent to the client. The information contains names of each node in every level of the hierarchical tree. The web service uses ADOMD to send XMLA Discover messages to retrieve the metadata from the OLAP server.



Figure 7. Gender dimension and its hierarchy

2.2.2 Cell Ordinals

After downloading the required metadata, XMLA is used to retrieve sub-cubes with the lowest level (the leaves of the hierarchy tree) of aggregation possible to perform aggregations such as cross-tab, drill-down and roll-up later by the client or the application server. The SOAP web service receives an MDX query (figure 8) created by the client.

SELECT {[Measures].[Internet Sales Amount]} on axis(0), DESCENDANTS([Customer].[Education].[All Customers],,LEAVES) on axis(1), DESCENDANTS([Geography].[Geography].[All Geographies],,LEAVES) on axis(2) FROM [Adventure Works]

Figure 8. MDX query for lowest level of aggregation

Since our goal is to minimize the amount of data sent over the network, we do not create a fact table (figure 9). Therefore we do not use ADOMD to execute this query (figure 8) because ADOMD produces a fact table from the results of the XMLA execute message.

	[Geography].[Geog	[Geography].[Geog	[Geography].[Geog	[Geography].[Geog Code].[MEMBER_([Customer].[Educat	[Measures].[Interne Sales Amount]
	Australia	New South Wales	Alexandria	2015	Bachelors	9900142.7571
	Australia	New South Wales	Alexandria	2015	Graduate Degree	5460560.2513
	Australia	New South Wales	Alexandria	2015	High School	4638026.0686
l	Australia	New South Wales	Alexandria	2015	Partial College	7723542.8848
	Australia	New South Wales	Alexandria	2015	Partial High School	1636405.2589
-	Australia	New South Wales	Coffs Harbour	2450	Bachelors	9900142.7571
Ī	Australia	New South Wales	Coffs Harbour	2450	Graduate Degree	5460560.2513

Figure 9. Fact table

Instead we use XMLA directly to execute this MDX query (figure 8). XMLA executes this query by embedding it in an Execute message. This query returns the leaves of each dimension's hierarchy tree (Figure 10), which are represented by a list of cells.



Figure 10. Hierarchy tree leaves selection

The result of the query is shown in figure 11. Each cell represents an element in the Cartesian product of the dimensions. Each cell is identified by an integer called *CellOrdinal* and is assigned to a numerical value from the measures.

<Cell CellOrdinal="0"> <Value xsi:type="xsd:double">9900142.7571</Value> <FmtValue>\$9900142.7571</FmtValue> </Cell> <Cell CellOrdinal="1"> <Value xsi:type="xsd:double">5460560.2513 </Value> <FmtValue>\$5460560.2513 </FmtValue> </Cell>

Figure 11. Query result

Since the result of a XMLA query execution is highly detailed, we parse the result to retrieve only the numerical values such that the amount of data transmitted over the network is minimized. This list of numerical values becomes the sub-cube (figure 12) that will be sent to the client in the client-centric architecture. We call this list of numerical values the *cell table*.

9900142.7571	
5460560.2513	
4638026.0686	
7723542.8848	
1636405.2589	
9900142.7571	
5460560.2513	

Figure 12. Cell table

2.3 SOAP Web Service

The web service component serves as a middleware between the client and the ADOMD layer. This component is created using ASP .Net. It uses Simple Object Access Protocol (SOAP) as the protocol for the exchange of structured information. SOAP uses XML as a message format and uses HTTP for message transmission.

The web service has two major functions. It receives requests from the client, which could be requests for metadata, or a query in MDX. It processes the results from ADOMD and XMLA before sending them to the client in the client-centric architecture.

2.4 Application Server

In the server-centric architecture, the application server is an extension of the web service component discussed in the last section. It receives query requests from the mobile thin client using SOAP as the message exchange protocol. However, it does not send the metadata and the sub-cube to the thin client. Instead, the application server uses the metadata and the sub-cube locally to compute OLAP operations such as cross-tab, top-k, and moving average before sending the results to the client.

3. MOBILE CLIENT IMPLEMENTATION

In this chapter, we explain the implementations of the mobile client in the clientcentric architecture and the mobile thin client in the server-centric architecture in sections 3.1 and 3.2, respectively. Then in section 3.3, we explain the implementation of the OLAP data engine. Finally in section 3.4, we explain the implementation of the OLAP visualization engine.

3.1 Mobile Clients in the Client-Centric Architecture

Mobile clients in the client-centric architecture are divided into two types: appbased and web-based. The app-based mobile client is implemented in Java and is installed in the Android operating system. Android is a popular mobile platform based on the Linux kernel. It includes the Dalvik virtual machine, libraries, middleware, and API's for mobile software development using Java. Figure 13 shows the architecture overview of Android.

An open-source library called kSOAP [22] allows the app-based client to connect to the SOAP web service. After using the web service to download a sub-cube with the lowest level of aggregation, the mobile client is responsible for all computations required by the user, in contrast to the thin client in a server-centric architecture. A screenshot of the app-based client is shown in figure 14.

		APPLICATIONS		
Home	Contacts	Phone	Browser	
	APPLI	CATION FRAME	WORK	
Activity Manager	Window Manager	Content Providers	View System	Notification Manager
Package Manager	Telephony Manager	Resource Manager	Location Manager	XMPP Service
	LIBRARIES		ANDROID	RUNTIME
Surface Manager	Media Framework	SQLite	Core L	ibraries
OpenGL ES	FreeType	WebKit	Daivik Mac	Virtual hine
SGL	SSL	libe		
		LINUX KERNEL		
Display Driver	Camera Driver	Bluetooth Driver	Flash Memory Driver	Binder (IPC) Driver
USB Driver	Keypad Driver	WiFi Driver	Audio Drivers	Power Management

Figure 13. Android architecture Overview [28]

Ma	ster										
LIST VIEW	GRID VIEW	тор-к	ACTIONS	SCATTER PLOT	MOVING AVERAGE	E					
Done											
[Account].	Account Nu	nber]									
[Account].	Account Typ	e]									
[Account].	[Accounts]										
[Customer].[City]										
[Customer].[Commute	Distance]									
[Customer].[Country]										
[Customer].[Customer]										
[Customer].[Customer	Geograph	yl								
[Customer].[Education]										
[Customer].[Gender]										
[Customer].[Home Owr	ner]									
[Customer].[Marital Sta	atus]									
Ĵ								ij.	- 1	 12:32	

Figure 14. App-based client screenshot

The web-based client is implemented in JavaScript and HTML to run in a web browser and is modified from [27]. For the performance evaluation in chapter 4, we use the Google Chrome web browser for Android. In contrast to the app-based client, the web-based client is not installed in the operating system. The web-based client uses the standard XMLHttpRequest to connect to the SOAP Web Service in order to download the metadata and the cell table. Figure 15 shows a screenshot of the web-based client running in the Chrome browser.

← → C S webolap.cmpt.sfu.ca:2000/v4/start.htm Server: Localhost ▼ Catalog: Adventure Works DW 2008R2 ▼ Cube: Adventure Works ▼ Expected Dataset Size 0 Hierarchy Selection: ▼ Get Subcube Set Column Set Measure Bind Slider Sort Subcube m-Day Moving Average	Ų į
Server: Localhost Catalog: Adventure Works DW 2008R2 Cube: Adventure Works Expected Dataset Size 0 Hierarchy Selection:	
SVG Scatterplot Canvas Scatterplot Top-k Contribution	/Advent
Dimension/Hierarchy: Dimension/Hierarchy: Account Customer Date Delivery Date. Delivery Date. Department Department Destnation Currency Employee Geography Internet Sales Order Details Product	

Figure 15. Web-based client screenshot

Since mobile devices such as smartphones and tablets have less memory than powerful desktop machines, it is important for applications to consume less memory. For this reason, Android's Dalvik virtual machine sets an upper limit for heap memory per application. For example, most tablets have at most 48mb of heap memory available for each application. During runtime, the heap grows dynamically as the Dalvik virtual machine requests more memory when needed.

In contrast to the app-based client, the web-based client running inside a browser is not limited by the Dalvik virtual machine. Therefore, the web-based client has access to more heap memory compared to the app-based client.

The human user begins to use the mobile client by selecting two dimensions from a list. Then the mobile client downloads the metadata and the sub-cube from the web service. Lastly, the mobile client performs OLAP operations using its data engine before presenting the resulting data visualizations to the user.

3.2 Mobile Thin Client in the Server-Centric Architecture

The mobile thin client is implemented in Java as an app just like the app-based client in the client-centric architecture. It also communicates with the server using the same SOAP library. The thin client has the same functions available to the user as the mobile client in the client-centric architecture. However in contrast to the client-centric architecture, the thin client does not download any metadata or sub-cubes. It also does not have a data engine; it only has a visualization engine. Instead, the thin client relies on the data engine of the application server for all computation. Its only job is to present the results from the application server to the human user using its own visualization engine.

3.3 OLAP Data Engine

The OLAP data engine implements several common OLAP operations: Cross-tab, drill-down, roll-up, and pivot. We only explain the cross-tab in this section since the other operations are either straightforward or similar to cross-tab.

3.3.1 Cross Tabulation

Cross tabulation (or cross-tab) is an aggregation of a measure based on dimensions. The values from one dimension form the row headers. The values from the second dimension form the column headers. The web service component returns a subcube with the lowest level of aggregation. Figure 16 shows this sub-cube represented as a fact table for clarity. An example of a cross-tab on this fact table is displayed in figure 17.

	(Geography).(Geog	[Geography].[Geog	[Geography].[Geog	[Geography].[Geog Code].[MEMBER_([Customer].[Educat	[Measures].[Interne Sales Amount]
	Australia	New South Wales	Alexandria	2015	Bachelors	9900142.7571
	Australia	New South Wales	Alexandria	2015	Graduate Degree	5460560.2513
1	Australia	New South Wales	Alexandria	2015	High School	4638026.0686
j	Australia	New South Wales	Alexandria	2015	Partial College	7723542.8848
	Australia	New South Wales	Alexandria	2015	Partial High School	1636405.2589
	Australia	New South Wales	Coffs Harbour	2450	Bachelors	9900142.7571
ī	Australia	New South Wales	Coffs Harbour	2450	Graduate Degree	5460560.2513

Figure 16. Fact table with the lowest level of aggregation

		Bachelors	Graduate Degree	High School	Partial College	Partial High School
۲	Australia	396005710.284	218422410.052	185521042.744	308941715.392	65456210.356
10	Canada	722710421.2682	398620898.3449	338575903.0078	563818630.5904	119457583.8997
	France	475206852.3408	262106892.0624	222625251.2928	370730058.4704	78547452.4272
Ĩ.	Germany	643509279.2114	354936416.3345	301471694.459	502030287.512	106366341.8285
	United Kingdom	524707566.1262	289409693.3189	245815381.6358	409347772.8944	86729478.72170
	United States	3722453676.669	2053170654.488	1743897801.7936	2904052124.684	615288377.3463

Figure 17. Cross-tab of Country and Education

The columns are from the Education dimension. The rows are from the Country level of the Geography dimension. The rows in figure 16 are aggregated based on their corresponding values for Country and Education. Rows with identical value for Country and identical value for Education are aggregated. For example, rows where the Country is Australia and the Education is Bachelors are added together to form the same entry in the resulting cross-tab. The resulting cross-tab is an M by N matrix, where M is the number of values in the first dimension and N is the number of values in the second dimension. Figure 18 shows the algorithm for cross tabulation.

```
Input: levelRow, levelColumn
Output: result table
index=0
rowLength=rows.length
colLength=columns.length
For i=0 to rowLength-1
    {
               currentRow=rows[i]
               if(levelRow>currentRow[0])
               {
                      index+=colLength
                      continue
               }
               row=currentRow[levelRow+1]*colLength
               For j=0 to colLength-1
               {
                      currentColumn=columns[j]
                      if(levelColumn<currentColumn[0]) //index 0 contains the number of indexes
                      {
                              resultTable[row + currentColumn[levelColumn+1]]+=CellTable[index]
                       }
                      index++
               }
     }
```

Figure 18. Cross-tab algorithm

The inputs are the levels of the cross-tab. For example in the cross-tab shown by figure 17, Country is level 1 in the Geography dimension's hierarchy and Education is level 1 in the Education hierarchy. Figure 19 shows a cross-tab of State-Province and Education. State-Province is level 2 in Geography's hierarchy and Education is still level 1.

		Bachelors	Graduate Degree	High School	Partial College	Partial High School
•	New South Wales	188102712.3849	103750644.7747	88122495.3034	146747314.8112	31091699.9191
	Queensland	79201142.0568	43684482.0104	37104208.5488	61788343.0784	13091242.0712
	South Australia	29700428.2713	16381680.7539	13914078.2058	23170628.6544	4909215.7767
	Tasmania	9900142.7571	5460560.2513	4638026.0686	7723542.8848	1636405.2589
į	Victoria	89101284.8139	49145042.2617	41742234.6174	69511885.9632	14727647.3301
_	Alberta	19800285.5142	10921120.5026	9276052.1372	15447085.7696	3272810.5178
	British Columbia	287104139.9559	158356247.2877	134502755.9894	223982743.6592	47455752.5081

Figure 19. Cross-tab of State-Province and Education

This algorithm uses indexes, downloaded from the web service component, to obtain a quick reference to the result table. Each leaf of the hierarchy tree contains the references. Figure 20 shows the indexes for the Education dimension. When the level is 1 for Education, there are five columns in the result table. The indexes are 0,1,2,3, and 4. When the level is 0 for Education, there is 1 column in the result table. As a result, the index is 0 for all leaves.



Figure 20. Metadata indexes.

3.3.2 Parallel Cross Tabulation

The newest generation of smartphones and tablets has dual-core or quad-core processors. The ASUS Transformer Prime has a quad-core processor capable of running multi-threaded applications in parallel. Computing the cross tabulation in parallel may lead to further improvements in performance for the app-based client.

Fortuna et al. conducted a study on the potential parallelism of JavaScript applications by examining dependency types and looping behavior [29]. The potential speedup averages 8.9 times and as high as 45.5 times. Unfortunately, there is no working implementation of data parallelism for JavaScript. HTML5 Web Workers [30] are independent processes that uses message passing for communication, instead of shared memory. Because the messages passed are copied, not shared, HTML5 Web Workers are unsuitable for parallelizing the cross-tab function. In addition, Intel Lab's River Trail project enables data parallelism in JavaScript web applications [31]. However, the project is currently at the prototype stage, and is not compatible with Android. Furthermore, WebCL is a JavaScript binding for heterogeneous parallel computing [32]. It is currently in development, and thus is unavailable for Android. For the above reasons, the web-based client is currently unable to fully utilize the hardware of mobile devices, in contrast to the app-based client.

Parallelization of cross tabulation for the app-based client can be done using the standard Thread library from Java. The algorithm for parallel cross-tab is shown in figure 21. The cell table is divided by the number of threads. Then each thread computes the cross-tab on a segment of the cell table. The parallel version of the cross-tab algorithm

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consumes more memory than the serial version since each thread must have its own result

table.

```
Input: levelRow, levelColumn, num
Output: result table
rowLength=rows.length
colLength=columns.length
size=rowLength/threads;
if(num==threads-1)
{
       start=num*size
       end=rowLength
}
else
{
       start=num*size
       end=start+size
}
index=start*colLength
For i=start to end
{
               currentRow=rows[i]
               if(levelRow>currentRow[0])
               {
                      index+=colLength
                      continue
               }
               row=currentRow[levelRow+1]*colLength
               For j=0 to colLength-1
               {
                      currentColumn=columns[j]
                      if(levelColumn<currentColumn[0])
                       {
                              resultTable[row +
                              currentColumn[levelColumn+1]]+=CellTable[index]
                       }
                      index++
               }
```

```
Figure 21. Parallel cross-tab algorithm
```

3.4 OLAP Visualization Engine

This section explains how the results of the data engine are presented to the user. After the computation of the cross-tab is completed, the results are displayed in a data grid. Section 3.4.1 explains the implementation of the data grid. However, advanced OLAP users require data visualizations that are more complex than a simple data grid. The sections from 3.4.2 to 3.4.4 explain three graphical data visualizations. These three graphical data visualizations are top-k percentage contribution, moving average, and scatter plot aggregation. Graphical data visualizations for the app-based client are implemented using AChartEngine [23], a Canvas graphical library for Android. Graphical data visualizations for the web-based client are implemented using vectorgraphic based libraries and the new HTML5 Canvas library.

3.4.1 Data Grid Implementation

This section describes the implementation of the data grid. Figure 22 shows a sample data grid created by the app-based client.

If the data is massive, slow rendering will block the user interface until it is completed. For this reason, the data grid is implemented using on-demand paging for both the web-based client and the app-based client. When the data grid is large, not all rows or columns are visible at the same time. When the user scrolls the data grid on a mobile device, new rows become visible, and certain rows disappear. Because creating a new row is an expensive operation, the data grid recycles the old rows that are no longer visible. The old rows are loaded with new data, and thus the application saves memory and CPU consumption by using a small data grid to display the large amounts of data.

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The web-based client implements the data grid using HTML table, and the appbased client implements the data grid using TextViews [33].

Ma	aster										
LIST VIEW	GRID VIEW	тор-к	ACTIONS	SCATTER PLOT	MOVING AVERAGE						
Roll Up	Drill Down	Roll Up	Drill Dow	n							
				Bache	lors	Female 5076191.3969	Male 4823951.3602				
				Graduate De	gree	Female 2819687.5061	Male 2640872.7452				
	High School		Female 2169808.4406	Male 2468217.628							
				Partial Col	ege	Female 3904283.7156	Male 3819259.1692				
				Partial High S	chool	Female 843647.616	Male 792757.6429				
Ĵ	\Box	Ū						-	÷	+]	12:35 🗣 🕌 » 🛔

Figure 22. Data grid

3.4.2 Top-K Percentage Contribution

Top-k percentage contribution ranks each value's contribution to the total sum of all the values during a certain time period. Then it returns the k values with the highest contributions. A realistic scenario of using top-k is the following. A user wants to find the top 10 best-selling products and their percentage contribution to the sales total during the last 30 days. First, the sales amount of each product during the last 30 days is aggregated. Then the running total of the sales amount of each product is ranked and the top 10 bestselling products are returned to the user. The result of the top-k computation is displayed in a table, as well as a pie chart. The web-based client renders the pie chart using *Google Chart Tools*, a SVG library [34]. The app-based client uses aChartEngine [23]. A slider allows the user to change the time period. Every movement of the slider triggers a function to re-computes the top-k percentage contribution. This function first computes a cross-tab on the sub-cube given the selected time period, and then ranks each value's contribution to the total sum of all the values. Because each movement of the slider triggers this function, the user may generate a large number of calculations in a short time period. Figure 23 shows what the results look like for top-k percentage contribution on the app-based client.



Figure 23. Top-k screen shot

3.4.3 Moving Average

The second graphical data visualization is moving average. A moving average analyzes a set of data by computing a series of averages of subsets of the data. Moving average is used in analysis of economic data. It is also used in financial applications.

The moving average we use is the simple moving average, which is the unweighted average of the previous n data points. We are given a series of numbers and a subset with a fixed size. The first moving average is computed as the average of the first subset of the number series. Then the subset is shifted forward to include a new data point and to exclude the first data point in the series. A new average is computed. This process repeats until the average of the last subset of the data series is computed.

For example, we want the simple un-weighted moving average in an n-day subset of sales amount. The first element in the moving average is the average sales amount of the first n days. If are the sales amounts for the first n days, then the formula for the first moving average is

$$SMA_{first \, day} = \frac{\sum_{i=1}^{n} S_i}{n}$$

Calculating the successive values is an inexpensive and simple operation. A new value is added to the previous summation and the oldest value is removed to form a new summation.

$$SMA_{today} = SMA_{last \ day} - \frac{S_{today-n}}{n} + \frac{S_{today}}{n}$$

Moving average is implemented as a line graph using *flot*, a Canvas library for the web-based client [35]. The app-based client uses aChartEngine [23]. An example of a simple moving average created by the web-based client is shown in figure 24.



Figure 24. Moving average screen shot

A playback function computes the moving average for the next day, and presents an animation as a way to observe trends in the moving averages of the data series. When the user starts the animation, the OLAP client calls the playback function to compute the moving average for the next day and continues to redraw the animation until it reaches the end of the data series.

3.4.4 Scatter Plot

Although data grid rendering performance is not a major problem when ondemand paging is implemented as shown by a previous section, the author in [24] argues that the amount of data in a large data grid can cause OLAP analysts to ignore important and interesting trends in the data. Graphical visualization tools provide an alternative platform to present OLAP data cubes and data [25, 26].

Scatter plot is a simple two variable graphical visualization tool for a set of data. The data is displayed as a series of points such that the position on the scatter plot is

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determined by the values for the two variables. The value of one variable determines a point's position on the horizontal axis and the value of the second variable determines a point's position on the vertical axis. The scatter plot is very useful for displaying the correlation of two variables. The correlations may be positive, negative, or the correlation does not exist. For OLAP, the two variables are two measures. An example of the scatter plot created by the web-based client is displayed in figure 25. The web-based client renders scatter plots by using *Protovis*, a SVG library [7]. The app-based client uses aChartEngine [23].



Figure 25. Scatter plot screen shot

An aggregation function has been implemented for the scatter plot by both the web-based and app-based clients. For example, the user drill-down on a region in the scatter plot by touch of the finger. When the region changes in size and position, the function aggregates the data points that are positioned within the user selected region on their x and y coordinates. This type of data analysis provides the ability to rapidly determine the contribution of a region of visible outliers in the data, and compare it with other selected regions in the scatter plot.

4. PERFORMANCE EVALUATION

In this chapter, we perform a performance evaluation of the client-centric architecture in section 4.1 and a performance evaluation of the server-centric architecture in section 4.2. The thin client in the server-centric architecture is app-based and we compare it with the app-based client of the client-centric architecture. The web-based client runs in the Google Chrome for Android web browser. The measure is [Internet Sales Amount].

The mobile device used for the performance evaluation is an ASUS Transformer Prime [8] tablet. This tablet has a 1.3 GHZ quad-core Nvidia Tegra 3 processor, and 1GB of main memory. Each core has 32KB L1 cache. The four cores share a 1MB L2 cache. It runs version 4.0.3 of the Android operating system. The server is equipped with four quad-core Intel Xeon E5420 processors and 4GB of memory. The web service is ASP .Net. The OLAP server is Microsoft Analysis Services 2008 R2.

4.1 Client-Centric Performance

In this section, we compare the app-based client and the web-based client on metadata download and parsing times, sub-cube download and parsing times, computing a cross-tab (a common OLAP operation), parallelization, data grid rendering, and graphical data visualizations.

4.1.1 Metadata Download and Parsing

After the human user selects a dimension, the mobile client sends a request for the metadata to the web service. After a dimension's metadata is downloaded, it is parsed. In

this section, we measure the download times of the metadata, and evaluate the parsing

times of the app-based and web-based clients. We use ten dimensions from the Adventure

Works data cube. The dimensions are [Geography].[Geography],

[Employee].[Employee], [Date].[DayOfYear],

[Date].[Calendar],[Reseller].[ResellerBank], [Customer].[Education],

[Reseller].[BankName], [Reseller].[OrderMonth], [Empolyee].[DepartmentName], and

[Empolyee].[Employee Department], respectively.

	Download Time	Web-Based	App-Based
	(ms)	Parse Time (ms)	Parse Time (ms)
Dimension #1	994	14	9
Dimension #2	915	6	4
Dimension #3	866	7	5
Dimension #4	967	104	33
Dimension #5	922	59	6
Dimension #6	584	3	0
Dimension #7	609	1	0
Dimension #8	526	0	0
Dimension #9	636	0	1
Dimension #10	871	13	4

Table 2. Meta information

Table 2 shows the download time and parsing time in milliseconds for each dimension. The download time is the same for both clients since they share the same web service and OLAP server. The app-based is able to parse the metadata faster than the

web-based client. However, because the download time is much greater in magnitude than the parsing time, the parsing advantage of the app-based client is not significant overall.

The download can be reduced in two ways. First of all, the SOAP Web Service could store the most recently requested metadata in a cache. Secondly, the metadata could be stored on the mobile client's internal storage.

4.1.2 Sub-Cube Download and Parsing

After the metadata are downloaded from the web service, the mobile client must download a sub-cube as a cell table from the web service. After a sub-cube is downloaded, it is parsed from a string into an array of floating point values. In this section, we measure the download times of the sub-cubes, and evaluate the parsing times of the app-based and web-based clients. We use five sub-cubes from the *Adventure Works* data cube.

The first sub-cube is composed of the dimensions [Date].[Day of Year] and [Geography].[Geography], which has 90885 tuples. The second sub-cube is composed of the dimensions [Geography].[Geography] and [Employee].[Employees], which has 163095 tuples. The third sub-cube is composed of the dimensions [Reseller].[ResellerBank] and [Employee].[Employees], which has 174549 tuples. The fourth sub-cube is composed of the dimensions [Geography].[Geography] and [Employee].[Employee Department],which has 193880 tuples. Finally, the fifth sub-cube is composed of the dimensions [Date].[Calendar] and [Employee].[Employees], which has 295812 tuples.

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Table 3 shows the download time and parsing time in milliseconds for each subcube. The download time is the same for both clients since they share the same web service and OLAP server. The app-based is able to parse the cell table about 2 to 3 times faster than the web-based client. However, because the download time is much greater in magnitude than the parsing time, the parsing advantage of the app-based client is not significant overall.

The download can be reduced in several ways. First of all, a number of OLAP servers have the option of optimizing at leaf level pre-aggregation. Second, the SOAP Web Service could store the most recently requested sub-cubes in a cache. Finally, the sub-cube could be stored on the mobile client's internal storage.

	Tuples	Download Time (ms)	Web-Based Parse Time (ms)	App-Based Parse Time (ms)
Sub-Cube #1	90885	6315	214	93
Sub-Cube #2	163095	8772	489	380
Sub-Cube #3	174549	11397	483	182
Sub-Cube #4	193880	10803	537	203
Sub-Cube #5	295812	15274	831	215

Table 3. Sub-cubes information

4.1.3 Cross Tabulation Evaluation

In this section, the web-based client is compared with the app-based client on the cross-tab computation. Performance is measured by the running time in milliseconds. Each experiment is run at least five times. Then, the average running time is used for the comparison. The performance of the two clients is compared on five sub-cubes of different sizes and hierarchical structures from the *Adventure Works* data cube. Detailed information on the five sub-cubes is found in table #3 in section 4.1.2.

The performance results are shown in figure 26. From the results, we can see that the app-based client computes a cross-tab significantly faster than the web-based client. Figure 27 shows the speedup gained by the app-based client. The running time of the app-based client is normalized with respect to the running time of the web-based client. The app-based client is around two times faster than the web-based client for all five subcubes. This is due to Java performing calculations faster than JavaScript.



Figure 26. Cross-tab performance comparison



Figure 27. Cross-tab speedup

4.1.4 Parallel Cross-Tab Evaluation

To evaluate the parallel version of cross-tab, we created three large sub-cubes. The first sub-cube has one million tuples. The second sub-cube has two million tuples. And the third sub-cube has three million tuples. Each tuple has the numerical value of 999999.99. We first run the serial algorithm from figure 18 and then the parallel cross-tab algorithm with three different values for the number of threads: two, three, and four. The running times, measured in milliseconds, are shown in figure 28 for the app-based client.



Figure 28. Cross-tab parallel performance

The speedup achieved by parallelization is displayed in figure 29. Computing the cross-tab in parallel can result in performance that is about three times faster than the serial algorithm for all three sub-cubes. For the first sub-cube in particular, the speedup is super linear when the number of threads is two or three.



Figure 29. Cross-tab parallel speedup

Figure 30 shows the efficiency of the parallel cross-tab algorithm. Parallel efficiency is defined as the speedup divided by the number of threads. When the number of threads is two, parallel efficiency is high for all three sub-cubes. Increasing the number of threads results in efficiency degradation, which is caused by contention for shared memory resources and communication bottlenecks.





Since the web-based client is unsuitable for data parallelism, we use its serial running time to compare it with the best running time of the app-based client. The running times in milliseconds are shown in figure 31 and the overall speedup for the app-based client over the web-based client is shown in figure 32. Overall, the app-based client is up to 4.81 times faster than the web-based client.



Figure 31. Web-based and parallel app-based cross-tab performance comparison



Figure 32. Parallel cross-tab speedup for app-based

4.1.5 Data Grid Evaluation

In this section, we compare the web-based and app-based clients on rendering the results of a cross-tab in a 2-dimensional grid. The web-based client requires 20 milliseconds to create a 6 by 9 grid, and the app-based client requires 30 milliseconds to

create the same grid. After creating the grid, the web-based client requires 3 milliseconds to load the data to the grid, and the app-based client requires 10 to 20 milliseconds to load the data to the grid. The reason loading the data is a slow operation for the app-based client is because setting the text of a TextView is slow. Therefore, the web-based is superior in displaying cross-tab results in a grid compared to the app-based client.

4.1.6 Top-k Percentage Contribution Evaluation

To evaluated the app-based client against the web-based client, we perform an experiment with three different values for k and the sub-cube with the dimension [Geography].[Geography] and the time dimension [Date].[DayOfYear] from the *Adventure Works* data cube. This sub-cube has 239075 tuples. The download time is 11466 milliseconds. The web-based client used 647 milliseconds to parse the sub-cube, and the app-based client used 200 milliseconds. The slider is moved from left to right to adjust the time period, and each slider movement recalculates the output. The average running time in milliseconds of the calculations is used for the comparison of the two OLAP clients. The performance results of the evaluations are displayed in figure 33 and figure 34 shows the speedup gained by the app-based client.

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Figure 33. Top-k performance comparison



Figure 34. Top-k speedup

From the results, we can see that the app-based client computes and renders the top-k percentage contribution faster than the web-based client. The running time of the app-based client is normalized with respect to the running time of the web-based client in figure 34. The app-based client is two to three times faster than the web-based client for all three values of k.

Table 4 shows the breakdown of the top-k running time in milliseconds. Rendering the pie chart is much slower for the web-based client, resulting in worse visualization smoothness compared to the app-based client. The rendering superiority of the app-based client is due to implementation of the Android graphics.

	Web-Based	App-Based
Pie Chart Rendering (ms)		
k=5	36.41	7.18
k=10	40.84	12.59
k=20	54.29	23.38
Top-K Calculation (ms)		
k=5	17.08	9.51
k=10	19.43	10.38
k=20	22.89	11.26
Total Running Time (ms)		
k=5	53.49	16.69
k=10	60.27	22.97
k=20	77.18	34.64

Table 4. Top-k running time break down

4.1.7 Moving Average Evaluation

To compare the web-based client and the app-based client on computing moving averages, we use the sub-cube with the dimensions [Customer].[Education] and [Date].[Day of Year] from the *Adventure Works* data cube. This sub-cube has 1825 tuples and requires 511 milliseconds to download. The web-based client requires 4 milliseconds to parse this sub-cube, and the app-based client requires 3 milliseconds. We use three variations for n, the size of the subset of the data series: 10 days, 20 days, and 30 days. The playback function is invoked a number of times to calculate each moving average. The average performance of the playback function, including the rendering time, is used to make a comparison of the two clients. The results, in milliseconds, are shown in figure 35.



Figure 35. Moving average performance in milliseconds



Figure 36. Moving average speedup

It is clear that the app-based client is five times faster than the web-based client for all three subset sizes as shown in figure 36. The app-based client computes a moving average and renders the result in 32 milliseconds. However, the web-based client computes the moving averages with a running time that is enough to cause the human visual perception to notice flicker. The rendering superiority of the app-based client is due to implementation of the Android graphics.

4.1.8 Scatter Plot Evaluation

In this section, we make a comparison of the web-based and app-based clients based on their performance in generating scatter plots, and on their performance in aggregating data points.

First of all, the web-based and app-based clients are evaluated on rendering small scatter plots: 10000, 20000, and 30000 points. The running times, measured in milliseconds, are shown in figure 37. And figure 38 shows the speedup gained by the

web-based client. The two clients perform roughly equal, with the web-based client









Figure 38. Scatter plot rendering speedup for web-based

Secondly, the web-based and app-based clients are evaluated on rendering large scatter plots: 100000, 125000, and 150000 points. The running times, measured in milliseconds, are shown in figure 39. And figure 40 shows the speedup gained by the

web-based client. The web-based client renders large scatter plots about three times faster than the app-based client. The app-based client is slower because it stores points in a dynamic data structure, and thus traversing a long array of points is a time consuming process.



Figure 39. Large Scatter plot rendering



Figure 40. Large Scatter plot rendering speedup for web-based

Finally, the two clients are compared on aggregating the data points in a scatter plot. The aggregation function is triggered on every *TouchMove* event to allow the user to

observe the differences of selecting neighboring points without making repetitive touch selections. As a result, the user may generate a large number of aggregations in a short period of time. Therefore, aggregation performance is important to the human user.

To evaluate the two clients on scatter plot aggregation, we use six sub-cubes from the *Adventure Works* data cube. The first sub-cube is composed of the dimensions [Reseller].[BankName] and [Date].[DayOfYear]. The second sub-cube is [Reseller].[OrderMonth] and [Date].[DayOfYear]. The third sub-cube is [Empolyee].[DepartmentName] and [Date].[DayOfYear]. The fourth sub-cube [Empolyee].[Empolyee] and [Date].[DayOfYear]. The fifth sub-cube is [Empolyee].[EmpolyeeDeparment] and [Date].[DayOfYear]. The sixth sub-cube is [Geography].[Geography] and [Date].[DayOfYear]. The detailed information of each sub-cube is shown in table 5. The two measures for the x and y axis are [Internet Sales Amount] and [Internet Order Quantity].

	Tuples	Points	Download Time (ms)	Web-Based Parse Time (ms)	App-Based Parse Time (ms)
Sub-Cube #1	5110	2555	839	29	9
Sub-Cube #2	9490	4745	1044	46	11
Sub-Cube #3	11680	5840	1156	40	11
Sub-Cube #4	181770	90885	8288	326	241
Sub-Cube #5	216080	108040	10074	497	132
Sub-Cube #6	478150	239075	21879	849	275

Table 5. Sub-Cube information for scatter plot aggregation

Figure 41 shows the running times of the clients, and figure 42 shows the speedup gained by the app-based client. The app-based client performs the aggregation function about four times faster than the web-based client, which results in smoother data visualization. This is due to Java performing calculations faster than JavaScript.



Figure 41. Scatter plot aggregation



Figure 42. Scatter plot aggregation speedup

4.2 Server-Centric Performance

The server-centric architecture has an application server that handles all computations requested by the thin client. The thin client is merely a graphical user interface that displays the results the application server sends.

The goal of this section is to compare the performance of the client-centric architecture with a server-centric architecture and show that performing successive calculations would create jitter for a server-centric system. The clients are app-based in both architectures and use the same graphics rendering library, aChartEngine [23]. In addition, we use the same sub-cubes as chapter 4.1. We evaluate the two systems on performing top-k and moving average. In the traditional server-centric architecture, the scatter plot is rendered on the server side and is sent to the thin client as a static image. As a result, the server-centric architecture does not allow the analyst to perform aggregations on a region in the plot. Therefore in this chapter, we do not evaluate the two architectures on performing a scatter plot aggregation.

The mobile thin client for the evaluation is subjected to two real-life network environments. The first location has higher network latency, while the second location has lower network latency.

4.2.1 Top-k Comparison with Client-Centric Architecture

This section compares the two architectures on performing the top-k percentage contribution. Since every movement of the slider triggers a function on the application server to re-computes the top-k percentage contribution, the number of queries is quiet large. Keeping up with the user would be difficult for the server-centric architecture in the presence of network latency. The response times, measured in milliseconds, are in figure 43. Figure 44 shows the speedup gained by the client-centric architecture. The network latency introduces an additional overhead to the response time, preventing the mobile client from rendering the visualization seamlessly without jitter. For the first location, the app-based client-centric system is almost twenty times faster than the server-centric system.



Figure 43. Top-k server-centric compared with client-centric



Figure 44. Top-k speedup for client-centric

4.2.2 Moving Average Comparison with Client-Centric Architecture

This section compares the two architectures on performing moving averages. In the server-centric architecture, when the user starts the play back function, the thin client requests the application server for the moving average of the next day. The additional network latency prevents the thin client from updating the visualization seamlessly, in contrast to the client-centric architecture. The response times, measured in milliseconds, are in figure 45. The speedup for the client-centric architecture is shown in figure 46. For the first location, the client-centric architecture is greatly superior to the server-centric architecture with a speedup as high as fourteen. Therefore, it is clear that the clientcentric architecture provides a much better user experience.



Figure 45. Moving average server-centric compared with client-centric



Figure 46. Moving average speedup for client-centric

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

With the emergence of powerful, multi-core mobile devices, OLAP applications are being developed for mobile software platforms. This project investigated and evaluated three OLAP architectures and environments for mobile devices: client-centric web-based, client-centric app-based and server-centric app-based.

First of all, we implemented an app-based OLAP client, and compared its performance with a modified web-based client. Although the web-based client is more convenient to use (it is not installed in the OS), it suffers from a performance penalty. Through experimentation, the web-based client was demonstrated to be inferior to the app-based client not only in performing a basic OLAP operation, but also in performing more complex, graphical visualizations, with a few exceptions. The app-based client computes a cross-tab in serial about two times faster than the web-based client, computes top-k percentage contributions two to three times faster, computes the moving averages about five times faster, and performs scatter plot aggregations about four times faster. In addition, the app-based client parses the metadata and sub-cubes downloaded from the web services faster than the web-based client. The few exceptions are rendering the data grid and the scatter plot, by which the web-based client is superior to the app-based client.

Secondly, we demonstrated the capability of the app-based client to compute a cross-tab on a recently introduced multi-core tablet. In contrast, we find it difficult for the web-based OLAP client to take advantage of the multi-core CPU. Since the web-based client lacks the software infrastructure to handle data parallelism, the app-based client

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using parallel computing is up to 4.81 times faster than the web-based client in performing cross-tabs.

In addition, we found out from our experience that the performance of the appbased system has more room for improvement than the web-based one. Initially, the parsing of the metadata and sub-cube for the app-based client is substantially slower than that for the web-based client. By switching to a different parsing method, the reverse is true. On the other hand, any substantial improvements in performance of web-based systems will depend on future revisions of HTML 5.

Finally, we used two graphical visualizations to argue for the superiority of the client-centric architecture over the server-centric architecture in performance. In contrast to previous research, we used two real-life network environments, instead of using simulated environments. The additional network latency prevents the thin client from updating the visualization seamlessly, in contrast to mobile client in the client-centric architecture.

5.2 Future Work

Improvements could be made to the web-based client. The HTML-based graphical libraries were proven to be inadequate in performing data visualizations relative to the app-based client. Perhaps performance could be improved if web-based client was implemented using Silverlight, which has hardware accelerated graphical libraries.

In addition, we could investigate how much improvement in scalability the clientcentric architecture provides to mobile OLAP.

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