

# **IMS to Big Data**

# **Common Traits for Success**

### Prepared for the: Virtual IMS User Group

### 4 October 2016

©Copyright SQData Corporation 2016 - All Rights Reserved

### **Objectives**

- $\blacktriangleright$  <u>**Primary</u>**  $\rightarrow$  Outline the Challenges with Streaming Mainframe to Big Data</u>
- Highlight the Top 5 Mistakes Customers Make
- Touch on the Current State of Big Data
- $\blacktriangleright$  Drill Down  $\rightarrow$  IMS to Big Data
  - ✓ CDC vs ETL
  - ✓ Streaming
  - Data / Design Considerations
- Recap Success Factors / Best Practices
- Address Any Questions that You May Have

# About Me

### Scott Quillicy

- ✓ 35 Years Database Experience
- ✓ Database Software Development
- ✓ Performance & Availability

### Founded SQData to Provide Customers with:

- ✓ A Better Way of Replicating Mainframe Data → Particularly IMS
- Solutions that Combine Consulting Expertise with Technology
- Technology Built Around Best Practices

### Specialization

- ✓ Database Trends and Direction
- ✓ Data Replication
- ✓ IMS to Relational
- ✓ Big Data Streaming
- Continuous Availability
- ✓ Data Analytics



### **About SQData**

Enterprise Class Data Replication

#### Specialization

- ✓ High-Performance Changed Data Capture (CDC)
- ✓ Non-Relational Data  $\rightarrow$  IMS, VSAM, Flat Files
- ✓ Relational Databases  $\rightarrow$  DB2, Oracle, SQL Server, etc.
- ✓ Big Data  $\rightarrow$  Hadoop, kafka, etc.
- Continuous Availability of Critical Applications
- Data Conversions / Migrations

#### Customer Use Cases

- ✓ Real-Time Data Streaming to Big Data
- ✓ Continuous Availability → Active-Active, Active-Passive
- ✓ Non-Relational (IMS / VSAM) to Relational
- ✓ ETL (Bulk Data Loads)
- Event Publishing / Notification
- ✓ Data Warehouse Feeds



# **Big Data**

>

>

>

#### What You May Have Heard...

- ✓ The "Solution to Everything Analytics"
- ✓ New Concept
- Adopt or Get Left Behind
- **Reality**  $\rightarrow$  Big Data has been Around for 50+ Years...

#### Characteristics

- Significant Amount of Data
- Advanced Analytics of Disparate Data
- ✓ Many Different Formats → Structured, Semi-Structured, Un-Structured
- ✓ Able to Handle a High Rate of Change

### Challenges

- ✓ Increasing Data Volumes → Stress Traditional RDBMS
- Computing and Infrastructure Costs to Process / Analyze
- Most Companies Still in Early Stages of Adoption

### Exciting Times Ahead

- Large Open Source Communities
- Rapid Evolution of Technology

### **You Have Several Options** → **More on the Way**



# Why Stream IMS to Big Data?

- Real Time Analytics
- Decisions based on Current Information vs 24+ Hour Old Data
- Quickly Detect Key Events / Trends
- Maintain a Competitive Advantage
- Provide Better Customer Service
- Increase Revenue / Profitability

# **Today's Popular Big Data Components**

### Hadoop HDFS

- Most Commonly Used Big Data Store
- Foundation Layer for other Technologies such as Spark
- ✓ Highly Scalable

### Spark

- High-Performance Processing Engine
- ✓ Extremely Fast and Versatile  $\rightarrow$  100x Faster than MapReduce
- Runs on HDFS or Standalone

### Kafka

- ✓ Ultra-Fast Message Broker
- Streams Data into Most Common Big Data Repositories
- Multiple Producers / Consumers

### Other Popular Stores

- ✓ DB2AA / PureData Analytics (Netezza)
- ✓ Cassandra
- Greenplum, Teradata
- ✓ MongoDB









mongoDB

# **Streaming IMS to Big Data**



# **IMS to Big Data** → **Common Pitfalls**

#### Lack of a Holistic Strategy

- ✓ "We Can Do it Ourselves" Approach
- Multiple Departments Going into Big Data with Small Projects
- ✓ Minimal Structure  $\rightarrow$  Methods, Tools, Support
- ✓ Significantly More Expensive → Time and \$\$\$

### Not Focusing on Business Needs

- "Build it and They will Come" Approach
- ✓ No *Clear* Use Cases
- ✓ Often Caused by Pressure to Deploy a Big Data Solution

### Data Collection Overkill

- "Everything Needs to be in Data Lakes" Approach
- Minimal Understanding of how to Relate the Data to Business Problems
- ✓ Spend a LOT of Time Moving Data of Little Value to the Business

#### Not Setting Proper Expectations

- ✓ 'We Can Have Something for You in No Time' Approach
- Guaranteed Project Timeline and Cost Overruns

### ➢ Understanding Mainframe Data → Particularly IMS

- ✓ "Just Take the Data and Copy it into Hadoop" Approach
- ✓ Non-Relational Nuances  $\rightarrow$  There are Many...

# **#1** → Approaching with a Holistic Strategy

#### $\blacktriangleright$ Key $\rightarrow$ Deploy on the Enterprise Platform

- Methodology More Mature
- Common Technology
- Centralized Support Model
- ✓ Faster Delivery  $\rightarrow$  Despite the "I/T Involvement is Too Much Red Tape"
- Reduced Costs



### Challenges

- ✓ Departmental Fiefdoms → "It's Our Budget...We'll do it Our Way"
- ✓ Everyone has a Different Opinion on What is the Best Option
- Departments May be in I/T Realm vs the Business

# **Product Selection**

### Repositories / Analytics

- ✓ Open Source
- Large Communities
- Proven Results
- Beware of Vendor Lock

#### ➢ Supporting Tools → ETL, Replication

- Typically Requires More than One
- ✓ Of Little Value if Source Data Not Understood
- ✓ Select the Best Tool for the Use Case  $\rightarrow$  i.e. Mainframe vs Twitter

### Licensing Model Considerations

- ✓ Typically Subscription Based → Traditional License + Maintenance on the Way Out
- ✓ Optimal  $\rightarrow$  Licensing Based on Business Use Case
- ✓ Should Be Able to Discontinue at Any Time  $\rightarrow$  No Long Term Commitment





# **Customer Examples**

#### ➢ Use Case → Sales Information into Big Data

- ✓ Tool Selection  $\rightarrow$  Cassandra
- ✓ Grew to 200 Nodes
- ✓ Project Cost  $\rightarrow$  2 Years and \$10M+
- Real-Time Updates were an Afterthought
- ✓ Result  $\rightarrow$  Failed  $\rightarrow$  Nobody is Using It
- ✓ Next Steps → Reworking by Enterprise Group into Hadoop / Spark

#### $\blacktriangleright$ Use Case $\rightarrow$ Financial Information into Big Data

- ✓ Tool Selection  $\rightarrow$  MongoDB
- ✓ Significant Amount of Data (multi-TB)
- ✓ Grew to 100 Nodes
- ✓ Project Cost  $\rightarrow$  1.5 Years and \$6M+
- Did Not Realize Mongo Does Not Scale Well Until it was Too Late
- ✓ Result  $\rightarrow$  Failed  $\rightarrow$  Not Usable
- ✓ Next Steps  $\rightarrow$  Trying to Migrate to Hadoop



mongoDB



# $#2 \rightarrow$ Focus on the Business Need

- $\blacktriangleright$  Key  $\rightarrow$  Business Users MUST be Involved from the Beginning
- Pressure to Deploy a Big Data Solution Plays a Role

#### Use Case Must be Clearly Defined

- Identify Source Data Elements
- ✓ Data Delivery  $\rightarrow$  Real Time vs Periodic ETL
- Success Criteria Fully Understood

### Leverage DevOps

- Data Scientists
- Business Analysts
- Technical Operations
- Quality Assurance

### Use an Agile Methodology

- Iterative Delivery
- Small, Achievable Milestones
- Start with Most Important Data
- Success Realized Sooner



# **Customer Examples**

### ➢ Use Case → Manufacturing Information to Big Data

- ✓ Tool Selection  $\rightarrow$  HBase
- ✓ Project Cost  $\rightarrow$  1.5 Years and \$7M+
- Data Dump without Understanding Relationships
- ✓ Result  $\rightarrow$  Failed  $\rightarrow$  Not Usable
- ✓ Next Steps  $\rightarrow$  Reworking by Enterprise Group and Business

### Use Case $\rightarrow$ Claim Information to Big Data

- ✓ Tool Selection  $\rightarrow$  MongoDB
- ✓ Project Cost  $\rightarrow$  2+ Years and \$10M+ (est)
- Data Dump without Understanding Relationships
- ✓ Result  $\rightarrow$  Failed  $\rightarrow$  Not Usable
- ✓ Next Steps  $\rightarrow$  Reworking by Enterprise Group and Business into Hadoop





# **#3** → Data Collection Overkill

#### ➢ Key → Focus on Important Business Data First

#### The Project that is Rarely Completed

- Similar to the Old Enterprise Data Warehouse
- Resource Intensive
- Success Criteria Fully Understood

#### Approach in Small Increments

- ✓ Realize Success Early
- Learn from Mistakes
- Manageable Costs and Time

#### Involve the Business

- They May "Want Everything"
- Identify Key Objectives
- Prioritize by Importance
- Leverage DevOps / Agile



# **Customer Example**

#### ➢ Use Case → Financial Institution

- ✓ Tool Selection  $\rightarrow$  Hadoop, kafka, Spark
- ✓ Project Cost  $\rightarrow$  2+ Years Until Project Cancelled
- ✓ Spent a LOT of Time Just Trying to Copy the Data  $\rightarrow$  with Mixed Results
- ✓ Result  $\rightarrow$  Failed  $\rightarrow$  Not Usable
- ✓ Next Steps  $\rightarrow$  Approach in Smaller Increments  $\rightarrow$  Leverage What Has Been Done



# #4 → Not Setting Proper Expectations

 $\blacktriangleright$  Reality  $\rightarrow$  Projects are at Least a 2 to 3 Year Effort

#### Relying on Estimates from Technical Folks

- Historically Optimistic
- Do Not Anticipate Obstacles
- ✓ Not Understanding Real-Time vs ETL
- ✓ Use the Tech Estimate x 2+

#### Success Can be Realized Early

- Small Subset of Important Data
- Assume DevOps / Agile
- Base Infrastructure in Place
- Technically Competent Team

#### Learn from Others

- ✓ Big Data User Groups
- Tech Conferences
- ✓ Consultants

 $\succ$ 



Source: https://gothinkbig.co.uk/

# **#5** → Not Understanding Mainframe Data

#### 

#### Common "I Had No Clue" Items

- IMS Structures in General
- Repeating Groups (Occurs)
- Redefines
- ✓ Dates
- Invalid Data
- ✓ 'Special' Fields (Bits, Y2K, etc.)
- Code Page Translation
- Transaction Consistency
- Streaming vs ETL
- Target Apply Concepts / Streaming
- Normalization vs Denormalization
- Is Not Likely to Get Better...



# **ACID vs BASE**

#### $\blacktriangleright \quad ACID \rightarrow Properties Guarantee DB Transactions are Processed Reliably$

- ✓ Atomicity  $\rightarrow$  All or Nothing...either the Transaction Commits or it Doesn't
- ✓ Consistency  $\rightarrow$  Transaction brings DB from One Valid State to Another
- ✓ Isolation  $\rightarrow$  Concurrency
- ✓ **D**urability  $\rightarrow$  Once a Transaction Commits, it Remains Committed
- $\blacktriangleright \quad BASE \rightarrow Eventual Consistency$ 
  - ✓ Basically Available  $\rightarrow$  Data is There...No Guarantees on Consistency
  - ✓ Soft State  $\rightarrow$  Data Changing Over Time...May Not Reflect Commit Scope
  - ✓ Eventual Consistency → Data will *Eventually* become Consistent

More Info: Charles Rowe - Shifting pH of Database Transaction Processing



Source: http://www.dataversity.net/acid-vs-base-the-shifting-ph-of-database-transaction-processing/

©Copyright SQData Corporation 2016 - All Rights Reserved

# **Common IMS Data Challenges**

### Code Page Translation

### Invalid Data

- Non-Numeric Data in Numeric Fields
- Binary Zeros in Packed Fields (or Any Field)
- Invalid Data in Character Fields

### Dates

- ✓ Must be Decoded / Validated if Target Column is DATE or TIMESTAMP
- ✓ May Require Knowledge of Y2K Implementation
- Allow Extra Time for Date Intensive Applications

### Repeating Groups

- ✓ Sparse Arrays
- Number of Elements
- ✓ Will Probably be De-normalized

### Redefines

#### Binary / 'Special' Fields

- Common in Older Applications Developed in 1970s / 80s
- Generally Requires Application Specific Translation

# **Additional Considerations**

#### Data Delivery / Latency

- Business Driven
- ✓ Full Extracts  $\rightarrow$  Periodic
- ✓ Near-Real-Time / Scheduled Updates

#### Workload Characteristics

- ✓ Read vs Update Ratio
- ✓ Update Volume  $\rightarrow$  Transaction Arrival Rate
- ✓ Will Effect Big Data Repository Selection

### Format

- ✓ Level of Normalization → Less is Usually Desirable
- Common Across Multiple Applications / Languages
- Level of Transformation Required

# The Role of ETL and CDC

#### ETL (Extract, Transform, Load):

- ✓ Full Data Extract / Load
- $\checkmark$  Data Transformation Logic Defined in this Step  $\rightarrow$  Reused by CDC
- ✓ Should be Run Against Live Data
- ✓ Should Minimize Data Landing



### **CDC (Changed Data Capture):**

- ✓ Move Only Data that has Changed
- ✓ Re-Use Data Transformation Logic from ETL
- ✓ Near-Real-Time / Deferred Latency
- ✓ Allows for Time Series Deliver



### **ETL and Changed Data Capture (CDC)**

### > ETL

- ✓ High Level of Control Over Level of De-Normalization
- Can Combine Many Segments in Target Row / Document
- ✓ Requires that ETL Tool can Handle Consolidation during Extract



#### **Changed Data Capture**

- May Dictate that Target not Fully Denormalized
- ✓ Capture Along One (1) Branch of IMS DB Record
- ✓ Path / Lookups *may* be Required

### **Target Apply Concepts**

### > Frequency

- ✓ Near-Real-Time
  - Continuous Stream
  - Low Latency  $\rightarrow$  Typically Sub-Second, but May be a Bit Higher for Larger Transactions
- ✓ Batches
  - Triggered by # Records and/or Time Interval
  - Time Based
  - Latency Varies

#### Time Series

- ✓ Analyze Data Changes Over Time
- ✓ All CDC Data is Inserted into Target
- ✓ timeuuid type Key

#### Incremental Updates (Synchronized)

- ✓ Source Matches Target
- ✓ Requires Query Adjustments for Insert-Only Targets (i.e. Hadoop HDFS)
  - Get Latest Image of Record by Key(s)
  - Filter Out Deletes
  - Merge into 'Master' File on Periodic Basis

### CDC / ETL Data Format(s)

#### ➢ Common Formats → JSON, Avro, Delimited, XML, Relational

#### JSON Recommended for CDC/ETL Data

- Especially for Data Lakes
- ✓ Records are Self-Described  $\rightarrow$  Encapsulated Metadata
- ✓ Payload Lighter than XML

Sample Update CDC Record in JSON Format

```
{"DEPT": {
  "database": "IMSDB01",
  "change op" : "U",
  "change time": "2015-10-15 16:45:32.72543",
  "after image" : {
     "deptno": "A00",
     "deptname": "SPIFFY COMPUTER SERVICE DIV.",
     "mgrno" : "000010",
     "admrdept" : "A00",
     "location" : "Chicago"
   },
  "before image" : {
     "deptno": "A00",
     "deptname": "SPIFFY COMPUTER SERVICE DIV.",
     "mgrno" : "000010",
     "admrdept" : "A00",
     "location" : "Dallas"
   }
}}
```

# $\textbf{Design} \rightarrow \textbf{Traditional IMS to Relational}$

- Each Segment Maps to One (1) or More Tables
- Strong Target Data Types May Require Additional Transformation
- Tendency to Over Design / Over Normalize
- Still Required for Relational Type Targets (DB2AA, Netezza, Teradata, etc.)



# **Design** $\rightarrow$ **IMS** to **Big Data**

- De- Normalized / Minimal Normalization
- Still Requires Transformation (dates, binary values, etc.)
- $\succ$ Good News → IMS Structure Already Setup for Big Data



### **IMS Data Capture Methods**

#### Primary Methods of Capture

- ✓ Data Capture Exit Routines
- ✓ Log Based

#### Database Capture Exit Routines

- ✓ Near-Real-Time for IMS TM/DB
- Extremely Fast and Efficient
- ✓ Scalability → Capture / Apply by FP Area, HALDB Partition, PSB, Database
- ✓ Do Not Require x'99' Log Records  $\rightarrow$  No Impact to IMS Logging

#### Log Based

- ✓ Near-Real-Time or Asynchronous
- ✓ CICS / DBCTL Environments
- ✓ Requires x'99' Log Records
- Scalability  $\rightarrow$  Same as Database Exit Routines

# **IMS Streaming**





# **Streaming to kafka**



### **Success Factor Summary** → **Best Practices**

#### Approach with a Holistic Strategy

- Common Infrastructure / Tools / Support
- Established Methods (DevOps / Agile)
- Beware the "Fiefdoms"

#### Involve the Business from the Start

- ✓ They Understand the Source Data
- They Know the Order of Importance
- ✓ They Can Assist in Design Validation, QA, etc.

#### Avoid the Data Collection Overkill

- ✓ Time and \$\$\$ Killer
- Focus on Most Important Data First
- ✓ Iterate through Remaining Data  $\rightarrow$  Prioritize by Importance

#### Set Proper Expectations

- ✓ 2 to 3 Years Minimum is Expected...for an Entire Project
- ✓ Deliver in Increments → Most Important Data First
- Understand the IMS Data is 'Special'
  - ✓ Patience is Key
  - ✓ Do Not Hesitate to Ask for Help...

# **Thank You!!**

©Copyright SQData Corporation 2016 - All Rights Reserved



# **IMS to Big Data**

# **Common Traits for Success**

### Prepared for the: Virtual IMS User Group

### 4 October 2016

©Copyright SQData Corporation 2016 - All Rights Reserved