# Big Data Architecture Lessons Learned

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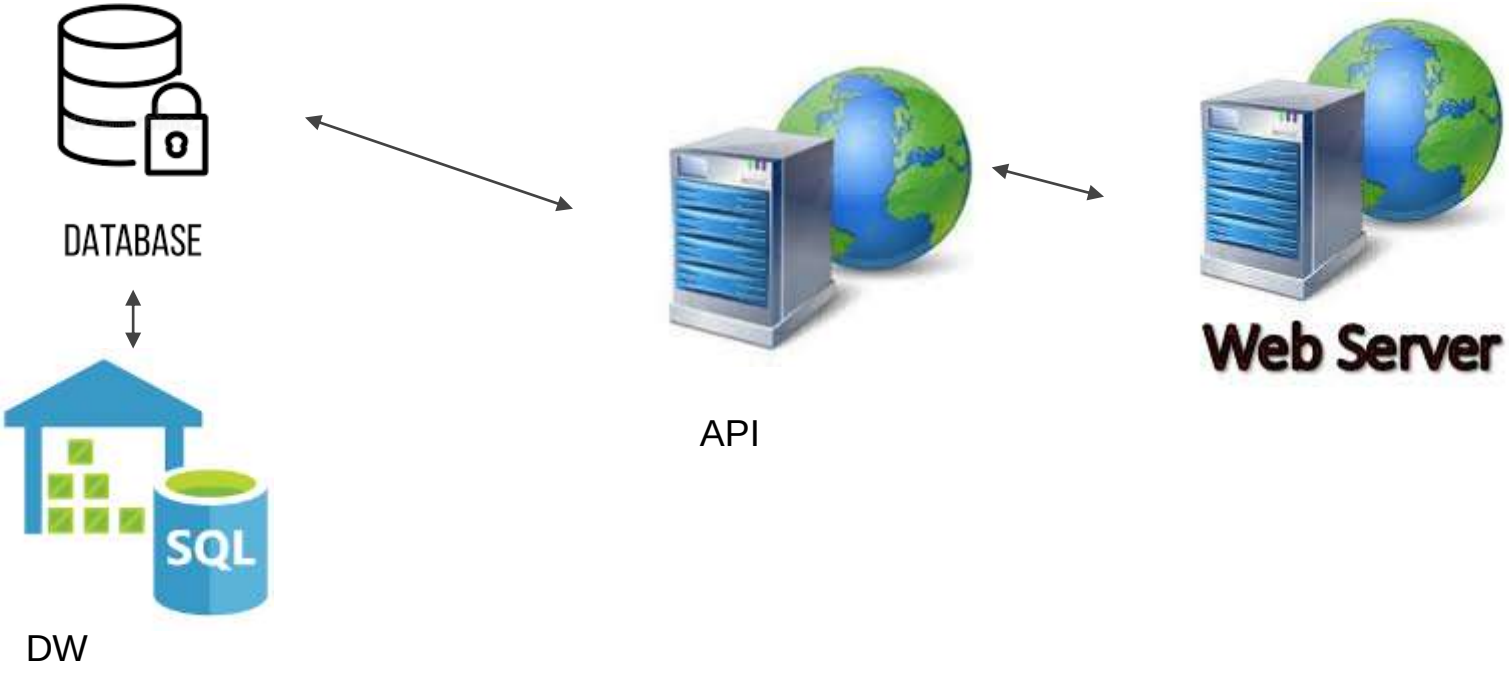
# In the past (web,api, ops db, data warehouse)



# When the data outgrows your ability to process

- Volume (100TB processing per day)
- Velocity (4GB/s)
- Variety (JSON, CSV, events etc)
- Veracity (how much of the data is accurate?)

# TODAY'S BIG DATA APPLICATION STACK
## PaaS and DC...

































MY BIG DATA APPLICATION STACK "demystified"...







Amazon S3

Amazon Athena






Apache Zeppelin

Amazon Kinesis






MY AWS BIG DATA APPLICATION STACK
With some “Myst”.

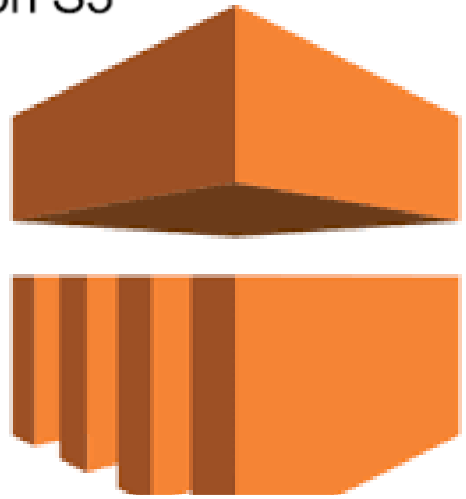







Amazon S3

Amazon Athena



Amazon Kinesis

Kinesis Streams

Kinesis Firehose

Kinesis Analytics

amazon
EMR

# Use Case 1: Analyzing browsing history

- Data Collection: browsing history from an ISP
- Product - derives user intent and interest  for marketing purposes.
- Challenges
  - Velocity: 1 TB per day
  - History of: 3M
  - Remote DC
  - Enterprise grade security
  - Privacy

# Use Case 2: Insights from location based data

- Data collection: from a Mobile operator
- Products:
  - derives user intent and interest  for marketing purposes.
  - derive location based intent for marketing purposes.
- Challenges
  - **Velocity: 4GB/s …**
  - Scalability: Rate was expected double every year...
  - Remote DC
  - Enterprise grade security
  - Privacy
  - **Edge analytics**

# Use Case 3: Analyzing location based events.

- Data collection: streaming
- Product: building location based audiences
- Challenges: **minimizing DevOps work on maintenance of a DIY streaming system**

# So what is the product?

- Big data platform that
  - collects data from multiple sources
  - Analyzes the data
  - Generates insights :
    - Smart Segments (online marketing)
    - Smart reports (for marketer)
    - Audience analysis  (for agencies)
- Customers?
  - Marketers
  - Publishers
  - Agencies

# My Big Data platform is about:

- Data **Collection**
  - **Online**
    - messaging
    - Streaming
  - **Offline**
    - Batch
    - Performance aspects
- Data **Transformation** (Hive)
  - JSON, CSV, TXT, PARQUET, Binary
- Data **Modeling** - (R, ML, AI, DEEP, SPARK)
- Data **Visualization** (choose your poison)
- **PII** regulation + **GPDR** regulation
- And: **Performance**... **Cost… Security… Simple**... **Cloud best practices**...

# Cloud Architecture Tips

- **Decouple** :
  - Store
  - Process
  - Store
  - Process
  - insight...
- **Rule of thumb: max 3 technologies in dc, 7  tech max in cloud**
  - Do use more b/c: maintenance
  - Training time
  - complexity/simplicity

# Big Data Architecture considerations

- unStructured? Structured? Semi structured?
- Latency?
- Throughput?
- Concurrency?
- Security Access patterns?
- Pass? Max 7 technologies
- Iaas? Max 4 technologies

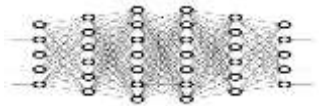
# Data ingestions Architecture challenges

- Durability
- HA
- Ingestions types:
  - Batch
  - Stream

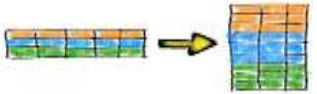
# Big Data Generic Architecture


Data **Visualization**

Data **Modeling** ( joins/agg/ML/R)



Data **Transformation** ( **row** to **colunar** + cleansing)



Data Collection
(file based ETL from remote DC)

# Big Data Generic Architecture | Data Collection


Data Visualization

Data Modeling

Data Transformation

Data Collection



# Batch Data collection considerations

- Every hour , about 30GB compressed CSV file
- Why s3
  - Multi part upload
  - S3 CLI
  - S3 SDK
  - (tip : gzip! )
- Why Client - needs to run at remote DC
- Why NOT your **own client**
  - Involves code →
    - **Bugs?**
    - **maintenance**
  - **Don't analyze data at Edge , since you cant go back in time.**
- Why **Not Streaming**?
  - **less accurate**
  - **Expensive**

# S3 Considerations

- Security
  - at rest: server side S3-Managed Keys (**SSE-S3**)
  - at transit: **SSL** / VPN
  - Hardening: **user, IP ACL, write permission only.**
- Upload
  - AWS **s3 cli**
  - **Multi part** upload
  - **Aborting Incomplete Multipart Uploads Using a Bucket Lifecycle Policy**
  - Consider S3 CLI **Sync** command instead of **CP**

# Sqoop - ETL

- Open source , **part** of **EMR**
- **HDFS** to **RDMS** and back. Via **JDBC**.
- E.g BiDirectional **ETL** from **RDS** to **HDFS**
- **Unlikely use case: ETL from customer source DB.**

# Flume & Kafka



- Opens source project for streaming & messaging
- Popular
- Generic
- Good practice for many use cases. (a meetup by it self)
- Highly durable, scalable, extension etc.
- **Downside : DIY, Non trivial to get started**

# Data Transfer Options

- VPN
- Direct Connect (4GB/s?)
- For all other use case
  - S3 multipart upload
  - Compression
  - Security
    - Data at motion
    - Data at rest
- bandwidth


# Quick intro to Stream collection

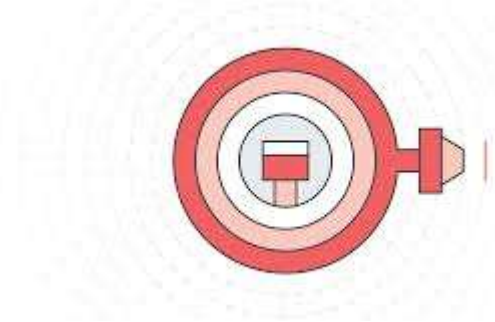
- Kinesis Client Library  (code)
- AWS lambda (code)
- EMR (managed hadoop)
- Third party (DIY)
  - **Spark streaming** (latency min =1 sec) , near real time, with lot of libraries.
  - **Storm** - Most real time (sub millisec), java code based.
  - **Flink** (similar to spark)

# Kinesis

- **Stream** - **collect@source** and near real time processing
  - **Near real time**
  - **High throughput**
  - Low cost
  - Easy administration - set desired level of capacity
  - Delivery to : s3,redshift, Dynamo, ...
  - Ingress 1mb, egress 2mbs. Upto 1000 Transaction per second.
  - Not managed!
- **Analytics** - **in flight analytics.**
- **Firehose** - Park you **data @ destination.**

# Firehose - for Data parking

- **Not for fast lane** - **no in flight analytics**
- Capture , transform and load.
  - Kinesis
  - S3
  - Redshift
  - elastic search
- Managed Service

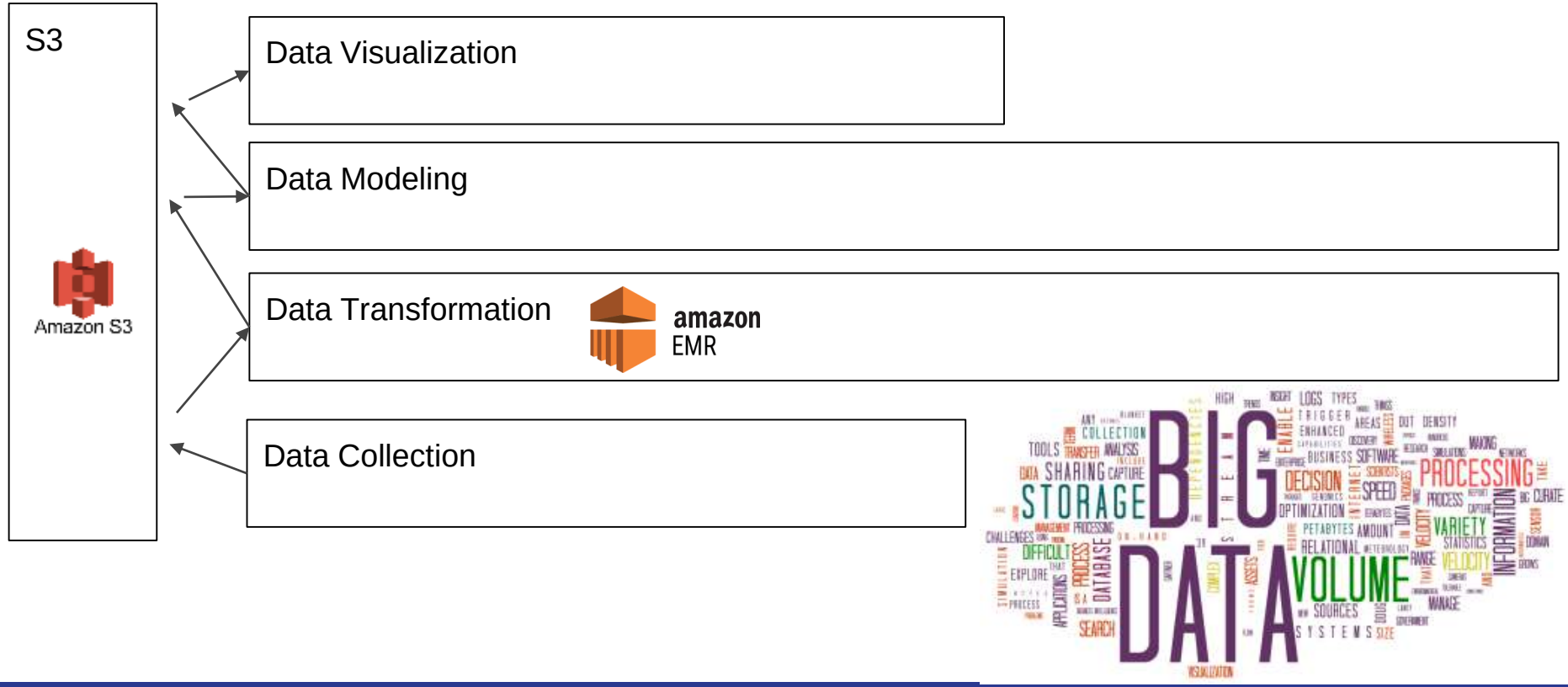


# Comparison of Kinesis product

- Stream
  - **Sub 1 sec processing latency**
  - Choice of stream processor (generic)
  - For smaller events
- Firehose
  - **Zero admin**
  - 4 targets built in (redshift, s3, search, etc)
  - **Buffering 60 sec minimum.**
  - For larger “events”

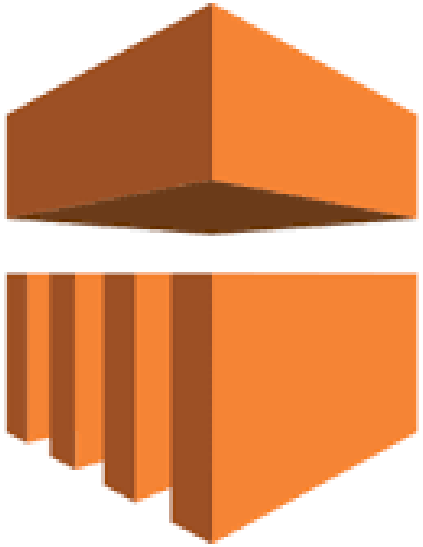
# Big Data Generic Architecture | Data Collection

# Big Data Generic Architecture | Transformation



# EMR ecosystem

- Hive
- Pig
- Hue
- Spark
- Oozie
- Presto
- Ganglia
- Zookeeper (hbase)
- zeppelin



amazon EMR

# EMR Architecture

amazon EMR

- Master node
- Core nodes - like data nodes (with storage: HDFS)
- Task nodes - (extends compute)
- Does Not have Standby Master node
- Best for transient cluster (goes up and down every night)

# EMR lesson learned...

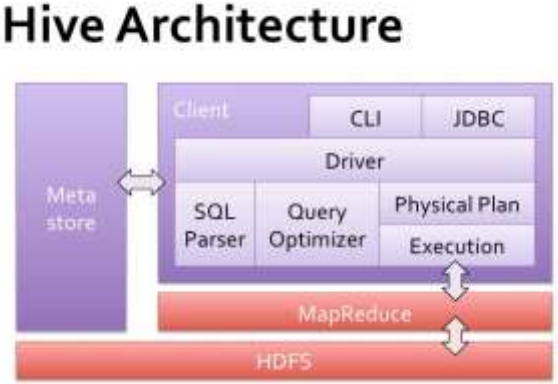
- **Bigger** instance type is good architecture
- Use **spot** instances - for the tasks.
- Don't always use **TEZ (MR? Spark?)**
- Make sure your choose instance with **network optimized**
- **Resize** cluster is not recommended
- **Bootstrap** to automate cluster upon provisioning
- Use **Steps** to automate steps on running cluster
- Use **Glue** to share Hive MetaStore

amazon EMR

# So used EMR for ... presto

- Most dominant
  - **Hive**
  - **Spark**
  - **Presto**
- And many more….
- Good for:
  - Data **transformation**
  - Data **modeling**
  - **Batch**
  - **Machine learning**






# Hive

- SQL over hadoop.
- Engine: spark, tez, MR
- JDBC / ODBC
- Not good when need to shuffle.
- Not peta scale.
- SerDe json, parquet,regex,text etc.
- Dynamic partitions
- Insert overwrite
- Data Transformation
- Convert to Columnar


# Presto

- SQL over hadoop
- Not good always for join on 2 large tables.
- Limited by memory
- Not fault tolerant like hive.
- **Optimized for ad hoc queries**
- No insert overwrite
- No dynamic partitions.

# Pig

- Distributed Shell scripting
- Generating SQL like operations.
- Engine: MR, Tez
- S3, DynamoDB access
- Use Case: for data science who don't know SQL, for system people, for those who want to avoid java/scala
- Fair fight compared to hive in term of performance only
- **Good for unstructured files ETL : file to file , and use sqoop.**

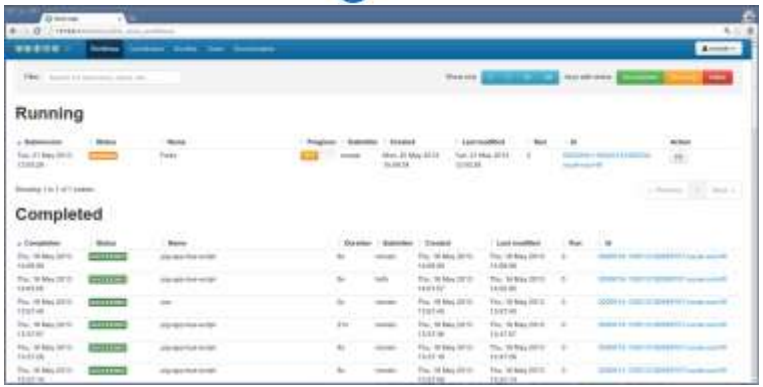
APACHE PIG

# Hue

- Hadoop user experience
- Logs in real time and failures.
- Multiple users
- Native access to S3.
- File browser to HDFS.
- Manipulate metascore
- Job Browser
- Query editor
- Hbase browser
- Sqoop editor, oozier editor, Pig Editor

# Orchestration

- EMR Oozie
  - Opens source workflow
    - Workflow: graph of action
    - Coordinator: scheduler jobs
  - Support: hive, sqoop , spark etc.
- Other: AirFlow, Knime, Luigi, Azkaban,AWS Data Pipeline




# Big Data Generic Architecture | Transformation

S3

Amazon S3

Data Visualization

Data Modeling

Data Transformation

Data Collection

# Big Data Generic Architecture | Modeling

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# Spark

- In memory
- X10 to X100 times faster
- Good optimizer for distribution
- Rich API
- Spark SQL
- Spark Streaming
- Spark ML (ML lib)
- Spark GraphX (DB graphs)
- SparkR


# Spark Streaming


- Near real time (1 sec latency)
- like batch of 1sec windows
- Streaming jobs with API
- **Not relevant to us...**

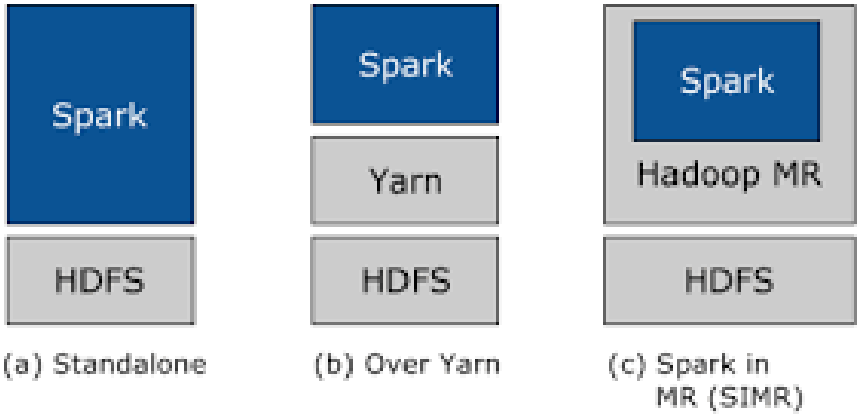

# Spark ML

- Classification
- Regression
- Collaborative filtering
- Clustering
- Decomposition
- Code: java, scala, python, sparkR


# Spark flavours

- Standalone
- With yarn
- With mesos






# Spark Downside


- Compute intensive
- Performance gain over mapreduce is not guaranteed.
- Streaming processing is actually batch with very small window.
- Different behaviour between hive and spark SQL

# Spark SQL

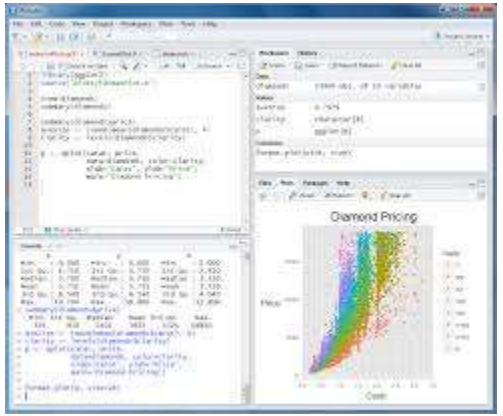
- Same syntax as hive
- Optional JDBC via thrift
- Non trivial learning curve
- Upto X10 faster than hive.
- Works well with Zeppelin (out of the box)
- Does not replaces Hive
- Spark not always faster than hive
- insert overwrite - not supported on partitions!

# Apache Zeppelin



- Notebook - visualizer
- Built in spark integration
- Interactive data analytics
- Easy collaboration.
- Uses SQL
- work s on top of Hive/ SparkSQL
- Inside EMR.
- Uses in the background:
  - **Shiro**
  - **Livy**

# R + spark R



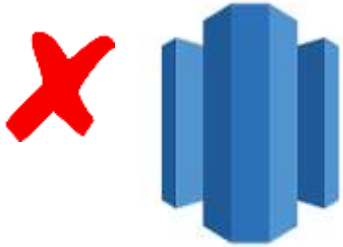

- Open source package for statistical computing.
- Works with EMR
- “Matlab” equivalent
- Works with spark
- Not for developer :) for statistician
- **R is single threaded - use spark R to distribute.**
- Not everything works perfect.

# Redshift

amazon REDSHIFT

- OLAP, not OLTP→ analytics , not transaction
- Fully SQL
- Fully ACID
- No indexing
- Fully managed
- Petabyte Scale
- MPP
- Can create slow queue for queries
  - which are long lasting.
- DO NOT USE FOR transformation.
- Good for : DW, Complex Joins.

# Redshift spectrum



amazon
REDSHIFT

Amazon S3

- Extension of Redshift, use external table on S3.
- Require redshift cluster.
- Not possible for CTAS to s3, complex data structure, joins.
- Good for
  - Read only Queries
  - Aggregations on Exabyte.

# EMR vs Redshift

- How much data loaded and unloaded?
- Which operations need to performed?
- Recycling data? → EMR
- History to be analyzed again and again ? → emr
- What the data needs to end up? BI?
- Use spectrum in some use cases. (aggregations)?
- Raw data? s3.



# Hive VS. Redshift

- Amount of concurrency ? low → hive, high → redshift
- Access to customers? Redshift?
- Transformation, Unstructured , batch, ETL → hive.
- Peta scale ? redshift
- Complex joins → Redshift



# Big Data Generic Architecture | Modeling

S3

Amazon S3

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# Big Data Generic Architecture | Visualize

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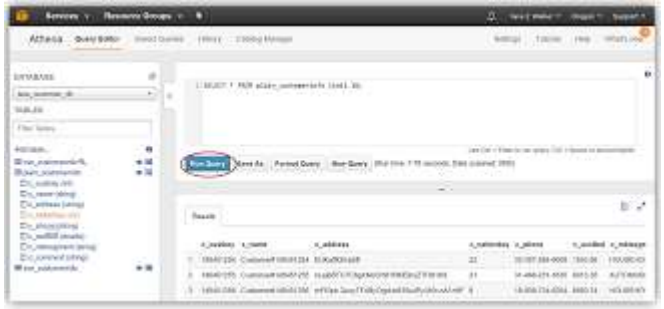
# Athena



Amazon Athena

- Presto SQL
- In memory
- Hive metastore for DDL functionality
  - Complex data types
  - Multiple formats
  - Partitions
- Good for:
  - Read only SQL,
  - Ad hoc query,
  - low cost,
  - managed

# Visualize

- QuickSight
- Managed Visualizer, simple, cheap

# Big Data Generic Architecture | Summary

S3

Amazon S3

Data Visualization

Amazon Athena

Data Modeling

amazon REDSHIFT

Spark SQL

Apache Zeppelin

Apache SHIRO

LEVY

Data Transformation

HIVE

hadoop YARN

hadoop HDFS

TEZ

HUE

OOZIE

Data Collection

sqoop

Java

Amazon Kinesis

Kinesis Streams

Kinesis Firehose

Kinesis Analytics

# Summary: Lesson learned

- Productivity of Data Science and Data engineering
  - Common language of both teams IS SQL!
  - Spark cluster  has many bridges: SparkR, Spark ML, SparkSQL , Spark core.
- **Minimize** the amount DB's used
  - Different **syntax** (presto/hive/redshift)
  - Different **data types**
  - **Minimize ETLS via External Tables+Glue!**
- Not always **Streaming** is justified (what is the business use case? PaaS?)
- **Spark SQL**
  - Sometimes **faster** than **redshift**
  - Sometimes **slower** than **hive**
  - Learning curve is **non trivial**
- Smart Big Data Architecture is all about:
  - **Faster, Cheaper, Simpler, More Secured.**