











AWS Big Data Demystified #1.2 Big Data Architecture Lessons Learned

Omid Vahdaty, Big Data Ninja























Disclaimer

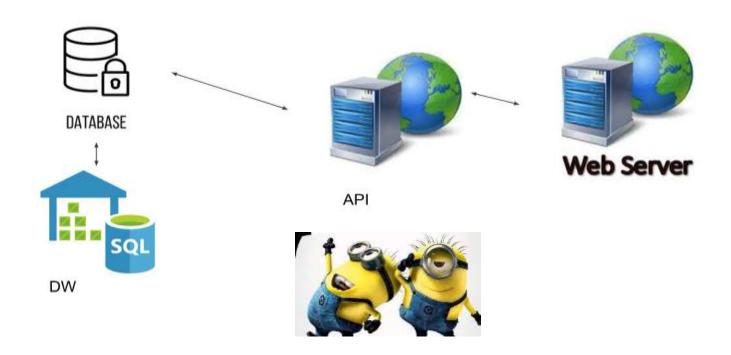
- I am not the best, I simply love what I do VERY much.
- You are more than welcome to challenge me or anything I have to say as I could be wrong.
- This Lecture has evolves over time, this is the 3nd iteration.
- Feel Free to send me comments



in a galaxy far, far away....

A long time ago

In the Past(web,api, ops db, data warehouse)



Then came Big Data...









TODAY'S BIG DATA **APPLICATION STACK**

PaaS and DC...















MESOS





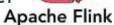


















































MY BIG DATA **APPLICATION STACK**























amazon

RDS





















MY AWS BIG DATA APPLICATION STACK With some "Myst".













DynamoDB

















Jargon

Big data?

Architecture?

Considerations?

Challenges?

How to get started?



Big Jargon & Basics concepts u should know

https://amazon-aws-big-data-demystified.ninja/2019/02/18/big-data-jargon-faqs-and-everything-you-wanted-to-know-and-didnt-ask-about-big-data/

- What is Big Data?
- scale out / up ?
- structured/semi structured/unstructured data?
- ACID?
- OLAP VS OLTP? == Analytics VS operational
- DIY = Do it Yourself
- PaaS = Platform as a service



Big Data = When your data outgrows your infrastructure ability to process

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



Challenges creating big data architecture?

- What is the business use case? How fast do u need the insights?
 - 15 min 24 hours delay and above \rightarrow use batch
 - Less than 15 min?
 - Might be batch depends data source is files or events?.
 - Streaming?
 - Sub seconds delay?
 - Sub minute delay?
 - Streaming with in flight analytics?
 - How complex is the **compute jobs?** Aggregations? joins?







Challenges creating big data architecture?

who decision substantial enge opportunity shaking when goals which which which when show here where which when show he when show he when show he when show he was shown as which we will be shown as whi

- What is the Velocity?
 - Under 100K events per second? Not a problem
 - Over 1M events per second? Costly. But doable.
 - Over 1B events per seconds? Not trivial at all.
- Volume?
 - ~1TB a day ? Not a problem
 - Over ? it depends.
 - Over a petabyte? Well.... It depends.
- Veracity (how are you going to handle different data sources?)
 - Structured (CSV)
 - Semi structured (JSON,XML)
 - Unstructured (pictures, movies etc)







Challenges creating big data architecture?

- Performance targets?
- Costs targets?
- Security restrictions?
- Regulation restriction? privacy?
- Which technology to choose?
- Datacenter or cloud?
- Latency?
- Throughput?
- Concurrency?
- Security Access patterns?
- Pass? Max 7 technologies
- laas? Max 4 technologies





Cloud Architecture rules of thumb...

Decouple :

- Store
- Process
- Store
- Process
- insight...

Rule of thumb: max 3 technologies in dc, 7 tech max in cloud

- o Do use more b/c: maintenance
- Training time
- complexity/simplicity









How to get started on big data architecture? Get answers to the below:

- 1. What is the business use case?
 - a. Volume? velocity? Variety? vercity/
 - b. Did you map all of data sources?
- 2. Where should we build a data platform?
 - a. What is the product? \rightarrow requirements.
 - b. Cloud? datacenter?
- 3. Architecture?
 - a. DIY? Paas?, Pay as you go? Or fixed? Decoupled?
 - b. Fast? Cheap? simple?
- 4. Did you Communicate you plans?
- 5. Did you map all known challenges?





Business Use Case?

CASE

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











I didn't choose this technology I choose this technology

Getting started

(notice the markings on upper right corner)

So what is the product?

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





Where to build the data platform?











We choose AWS because

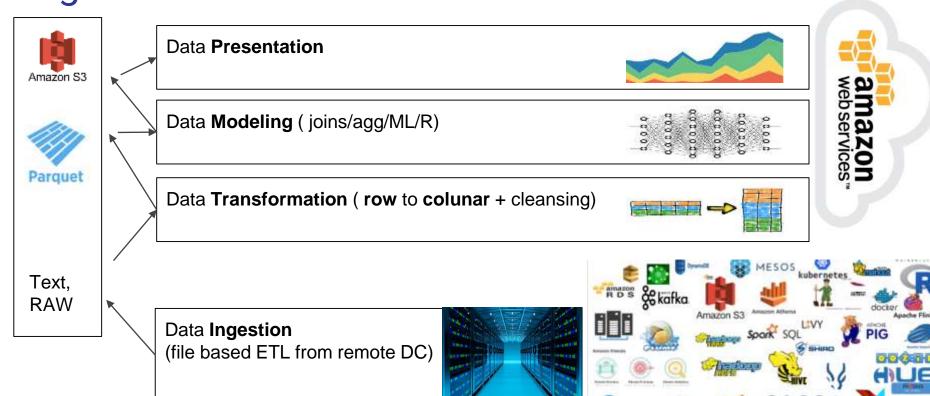
- After a long competitive analysis we choose AWS because, it seems to have all the relevant features For all our big data products and wallas publisher products
- The project was challenging enough, without adding the complexity of a learning curve (learning new cloud). We already knew how to work with AWS
- Of course, there business aspects as well.

My Big Data product does:

- Data Ingestion
 - 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...



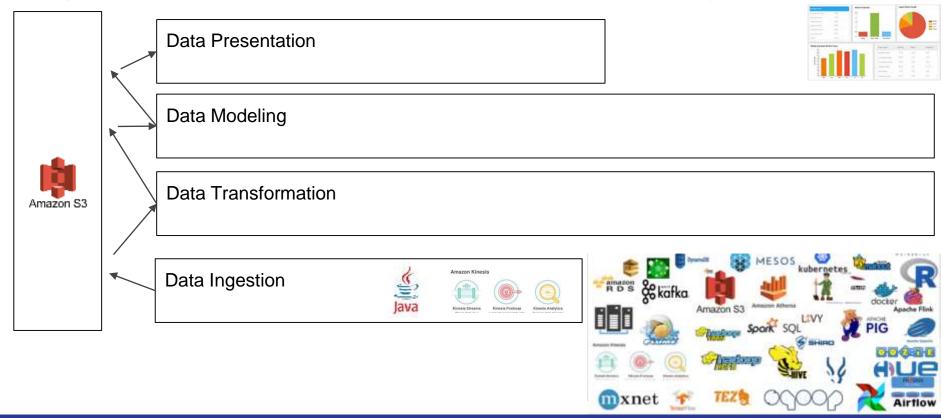
Big Data Generic Architecture



Data Ingestion

A layer in your big data architecture designed to do one thing: ingest data via Batch or Streaming, I.e move (only) data from point A to point B. from source data to the next layer in the architecture (decoupled).

Big Data Generic Architecture | Data Ingestion



Batch Data collection considerations

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







S3 Considerations

Security

- at rest: server side S3-Managed Keys (SSE-S3)
- o 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 operational 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

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







Quick intro to Stream ingestion

- 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.
 - o **Storm** Most real time (sub millisec), java code based.
 - o Flink (similar to spark)





Kinesis family of products

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

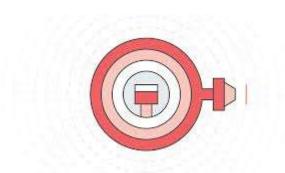






Kinesis Firehose - for Data parking

- Not for fast lane no in flight analytics
- Ingest , transform and load to:
 - Kinesis
 - o S3
 - Redshift
 - elastic search
- Managed Service





Comparison of Kinesis products

Streams

- 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"

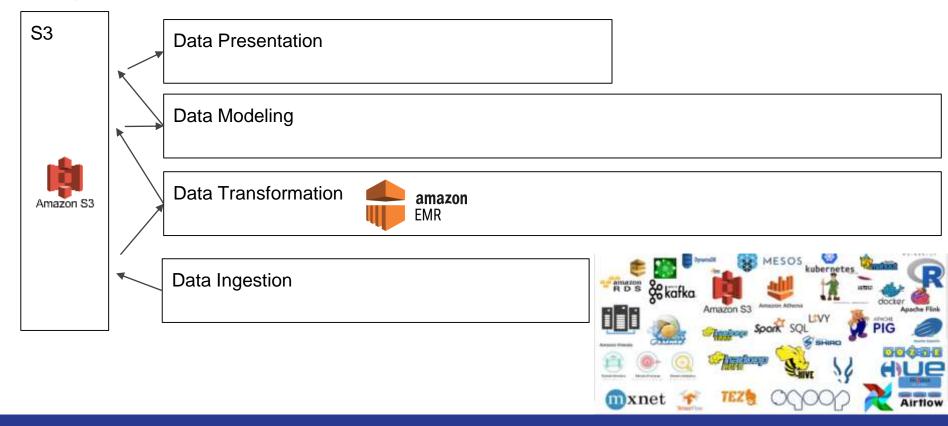




Data Transformation

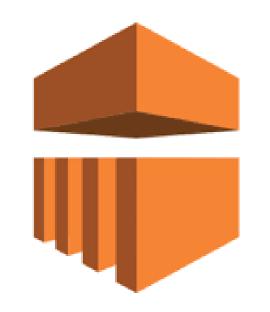
A layer in your big data architecture designed to: Transform and Cleanse data (row data to columnar data and convert data types, Fix bugs in data)

Big Data Generic Architecture | Transformation



EMR ecosystem

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







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 only.
- 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
- Good Cost reduction article on EMR





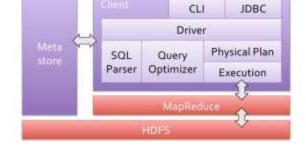


Hive Architecture

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















- 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.
- Has some connectors: redshift and more
- https://amazon-aws-big-datademystified.ninja/2018/07/02/aws-emrpresto-demystified-everything-youwanted-to-know-about-presto/







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.



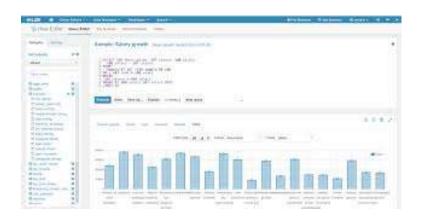


Hue

- 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









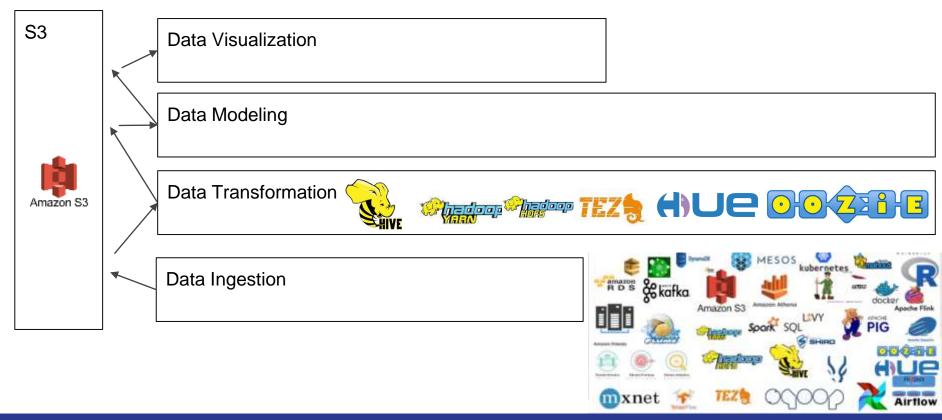


- EMR Oozie
 - Opens source workflow
 - Workflow: graph of action
 - Coordinator: scheduler jobs
 - Support: hive, sqoop, spark etc.
- Other options: AirFlow, Knime, Luigi, Azkaban, AWS Data Pipeline





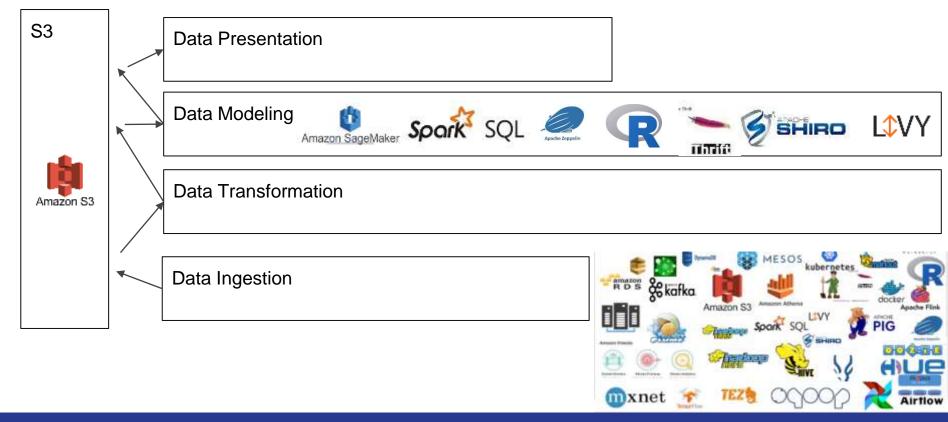
Big Data Generic Architecture | Transformation



Data Modeling

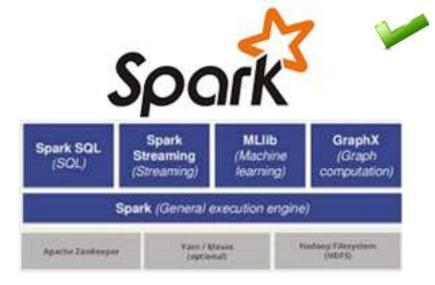
A layer in your big data architecture designed to Model data: Joins, Aggregations, nightly jobs, Machine learning

Big Data Generic Architecture | Modeling



Spark

- In memory
- X10 to X100 times faster from hive
- 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
- DIY = Not relevant to us...









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



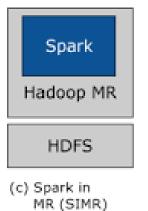


Spark flavours

- 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.



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 -







Apache Zeppelin

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



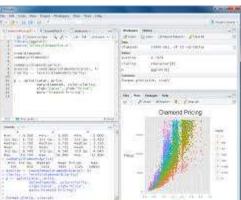






- Open source package for statistical computing.
- Works with EMR
- "Matlab" equivalent
- Works with spark
- Not for developer:) for statistician
- R is single threaded use spark R to distribute.
- Not everything works perfect.







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
- 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.
- When to use emr and when redshift?







Hive VS. Redshift

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





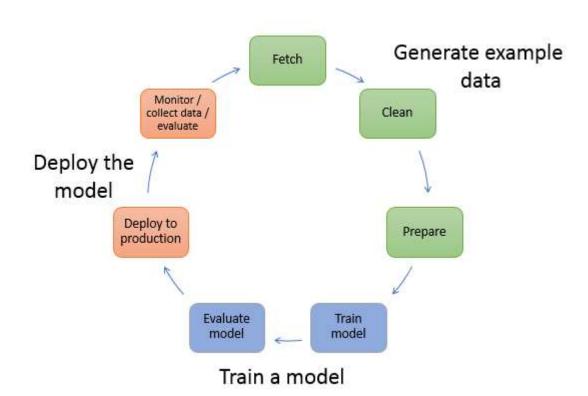






Sage Maker

- Web notebook (jupiter based) for data science
- Connects to all your data sources (s3,athena etc)
- Help you manage the entire lifecycle machine learning
- Managed Service
- Used to create a ML to predict cookie gender





AWS Glue

Shared meta store

Helps with some data transformation (managed service)

Automatic Schema discovery



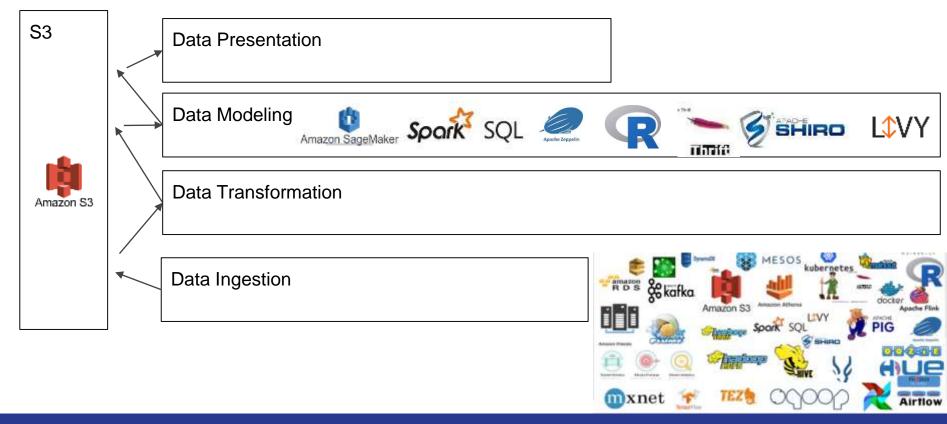


AWD RDS (aurora, postgres, mysql)

- We used RDS aurora as Operational DB
- We did not use it for big data analytics although it supports upto 64Tb
- It is row based.
- The syntax is missing analytical functions



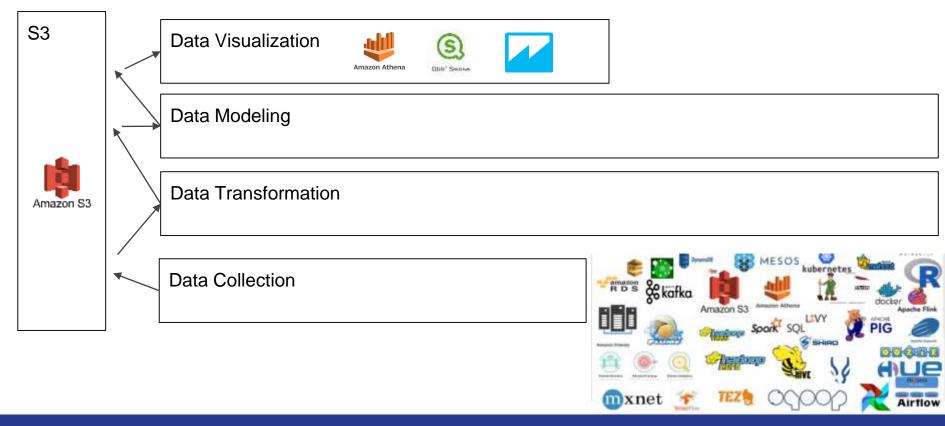
Big Data Generic Architecture | Modeling



Data Presentation

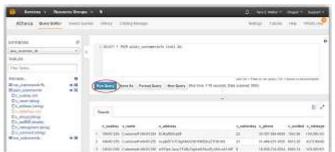
Used ONLY for presenting data for operational applications or BI, Use managed service to ensure HA.

Big Data Generic Architecture | Presentation



Athena

- Presto SQL
- In memory
- Hive metastore for DDL functionality
 - Complex data types
 - Multiple formats
 - Partitions
- Now supports CTAS (No inserts are supported)
- Good for:
 - Read only SQL,
 - Ad hoc query,
 - low cost,
 - Managed
- Good cost reduction article on athena





Amazon Athena



Visualize

- QuickSight
- Managed Visualizer, simple, cheap









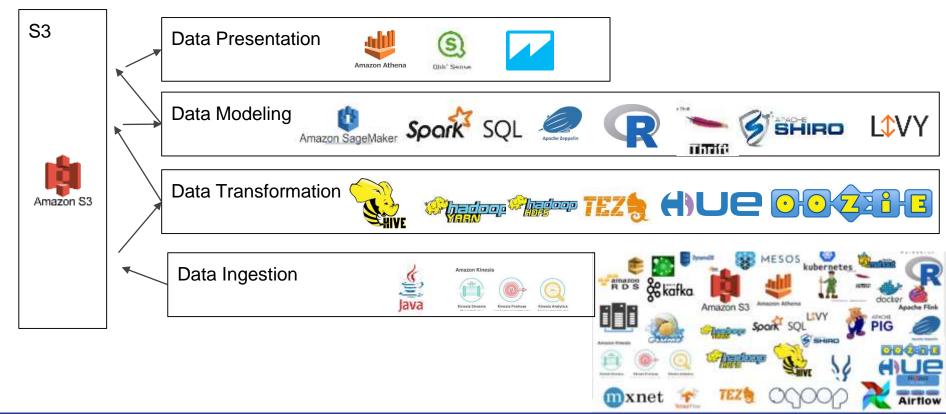




Summery

Take Away Message & Action Items

Big Data Generic Architecture | Summary



Summary: Lesson learned

- Decouple, Decouple
- Productivity of Data Science and Data engineering
 - Common language of both teams IS SQL!
 - Minimize the life cycle from dev to production of ETL and ML jobs
- 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



HORTONWORKS Cloudera

Summery: Common Q&A

- 1. Can this architecture be done on another cloud?
- 2. Redshift VS EMR?
- 3. Athena VS Redshift?
- 4. Cost reduction on EMR?
- 5. Cost Reduction on Athena?
- 6. Exporting data from Google Analytics into AWS?









Lesson learned: Big Data Architecture?

Faster!

Cheaper!

Simpler!







"Everything should be made as simple as possible. But not simpler."

-Albert Einstein



How to get started | Call for Action

Lectures: AWS Big Data Demystified lectures #1 until #4





AWS Big Data Demystified Meetup

Big Data Demystified meetup

Stay in touch...

- Omid Vahdaty in
- +972-54-2384178
- https://big-data-demystified.ninja/
- Join our meetups subscribe to youtube channels
 - https://www.meetup.com/AWS-Big-Data-Demystified/
 - https://www.meetup.com/Big-Data-Demystified/
 - Big Data Demystified YouTube
 - AWS Big Data Demystified YouTube
 - WhatsApp group



