

Organizations need to gain insight and knowledge from a growing number of Internet of Things (IoT), APIs, clickstreams, unstructured and log data sources. However, organizations are also often limited by legacy data warehouses and ETL processes that were designed for transactional data. In this session, we introduce key ETL features of AWS Glue, cover common use cases ranging from scheduled nightly data warehouse loads to near real-time, event-driven ETL flows for your data lake. We discuss how to build scalable, efficient, and serverless ETL pipelines using AWS Glue. Additionally, Merck will share how they built an end-to-end ETL pipeline for their application release management system, and launched it in production in less than a week using AWS Glue.

Today's Agenda

Intro to AWS Glue

Construct an ETL flow in 4 steps

Under the hood: customize AWS Glue scripts

Merck - customer testimonial

We are going to see how we can build data transformation pipelines with AWS Glue. We will see how we can construct an ETL flow in Glue from raw unfiltered data to an ETL flow running in production in 4 easy steps.

What is AWS Glue?

Fully-managed, serverless extract-transform-load (ETL) service

for developers, built by developers

1000s of customers and jobs

Select AWS Glue customers

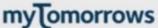
















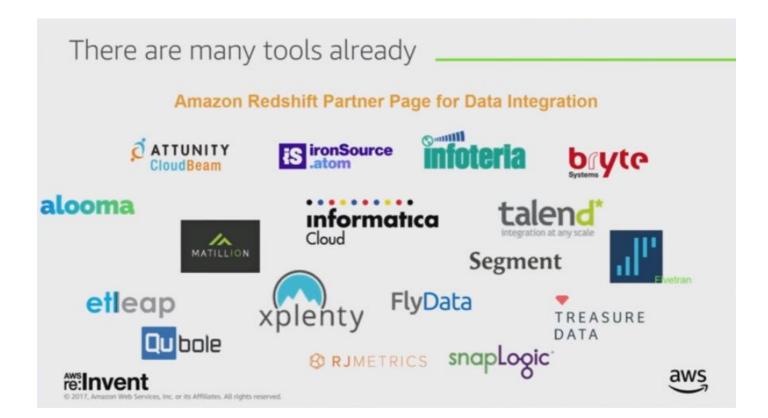


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Still, ETL developers hand-code

Canvas-based tools are hard to extend

Code is flexible, powerful, and easy to share

Familiar tools and development pipelines

IDEs, version control, testing, continuous integration

This talk is for developers!

Hand-coding is laborious

schemas change data formats change add or change sources data volume grows

makes hand-coding error-prone & brittle

AWS Glue does the undifferentiated heavy lifting so developers can easily customize

AWS Glue Components



Data Catalog

Discover

Automatic crawling

Apache Hive Metastore compatible

Integrated with AWS analytic services



Job Authoring

Develop

Auto-generates ETL code

Python and Apache Spark

Edit, Debug, and Explore



Job Execution

Deploy

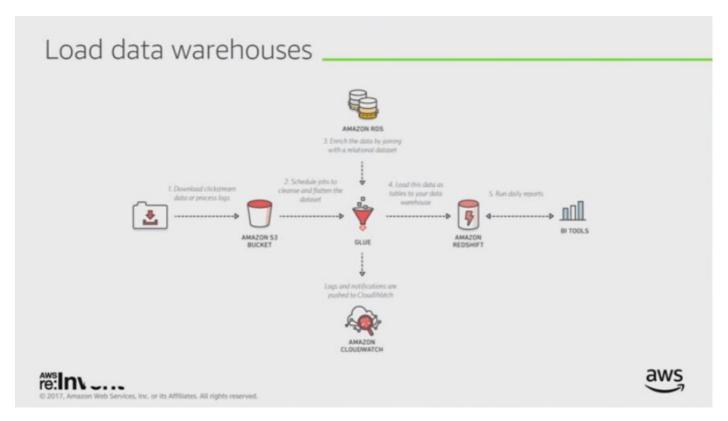
Serverless execution

Flexible scheduling

Monitoring and alerting

The *Data Catalog* helps you discover and understand the data sources that you have, we have crawlers that will automatically extract the data structure when you point them to one of your data sources and store all that information including statistics into the catalog for you. The *Job Authoring* and ETL component lets you get started quickly on your ETL job flow design, it generates Python/Spark code for you if you point it to tables and sources inside the data catalog. The *Job Execution* system is serverless and can turn your ETL code into a Job and then run it for you, you can also schedule the Jobs and monitor their progress.

Common use-cases



Customers get all their data from a variety of different places, integrate them together with AWS Glue, structure it, and then put it into Redshift for later analysis.



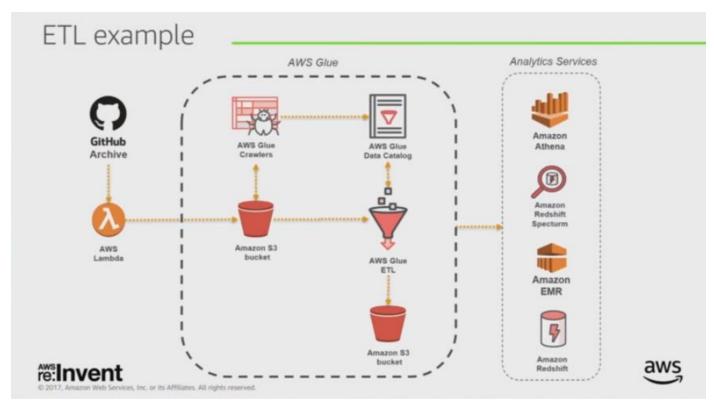
Customers are also building data lakes with Glue instead of warehousing their data. they crawl all their data, index all their information and make that data available for analysis using any of the available services like Athena, EMR, Redshift Spectrum.

Construct an ETL flow in 4 steps

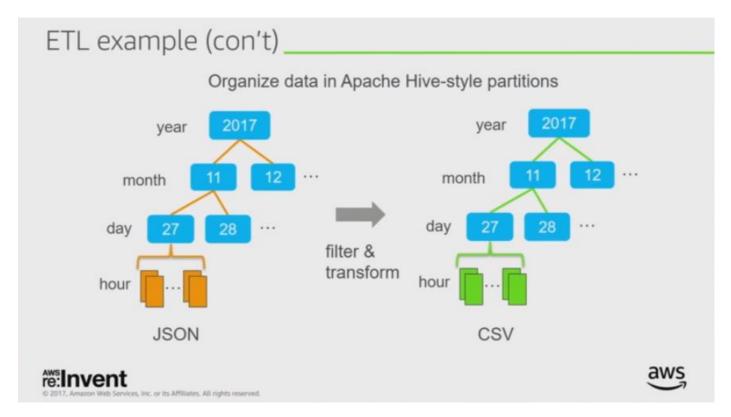
The 4 Steps

- 1. Crawl and catalogue your data
- 2. Specify mappings to generate scripts
- 3. Interactively edit and explore with dev-endpoints
- 4. Schedule a job for running in production

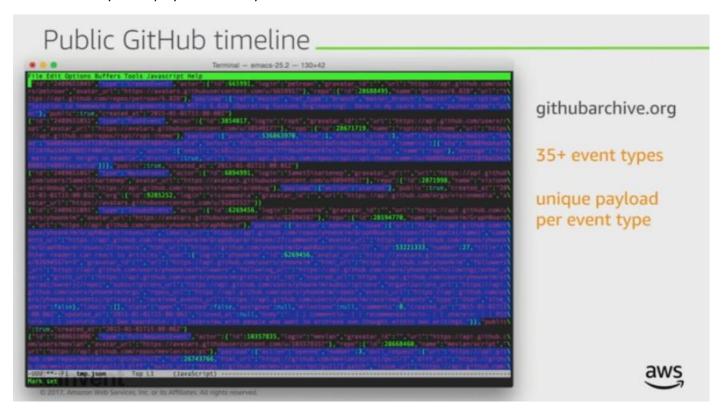
The first step is to point the crawlers and catalog to your data, the crawlers will then figure things out for you automatically. Once you have your data all indexed inside your catalog, you can specify mappings with the AWS Glue console that will then generate an ETL flow code for you. You can edit the generated code using development endpoints. Finally, you can schedule and trigger your jobs in a dynamic fashion.



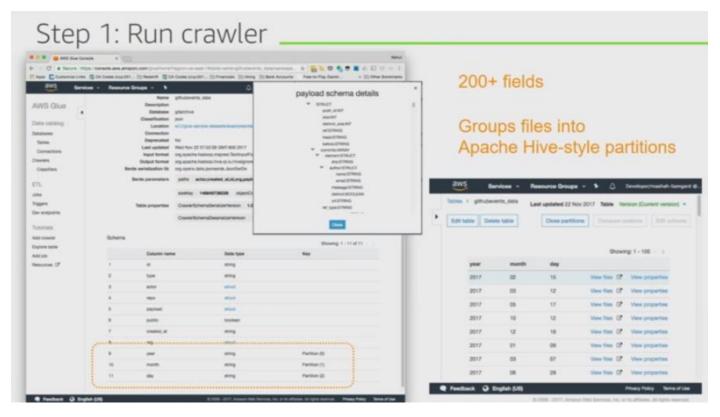
This is an example where we are going to be converting a bunch of JSON data to CSV, this is a typical job used when building data lakes and data warehouses. GitHub Archive is data generated in JSON form hourly for public view.



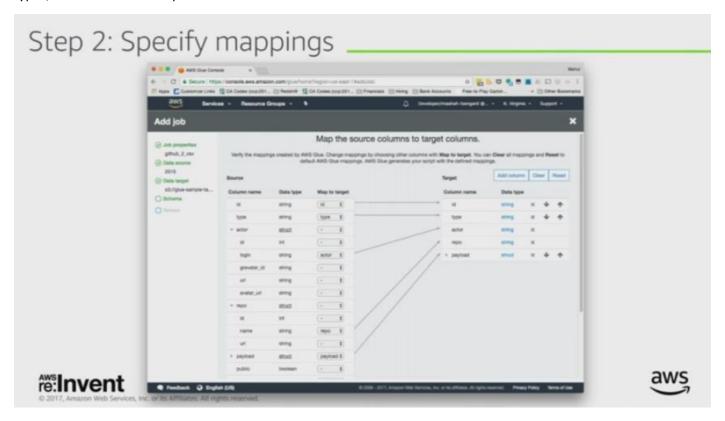
We need to organize the data into directory hierarchy in separate S3 buckets. We are going to be filtering the source JSON data on the left for specific events, transforming the data into CSV format, then try to get the data into the same kind of hierarchy to simplify further analysis.



This is the raw data, it includes about 37 event types with varying structure per event type

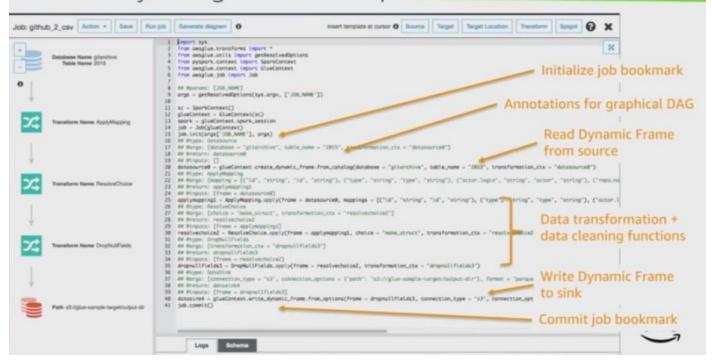


When you point the crawler to this data, it will generate the data schema for you automatically. It will detect the data types, fields and even complex schema structures.

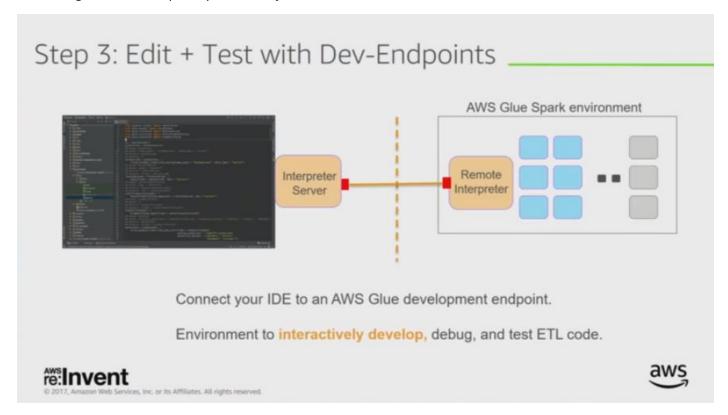


You can start converting the data using the Add Job Service to choose parts of the schema that we want to map from source to destination.

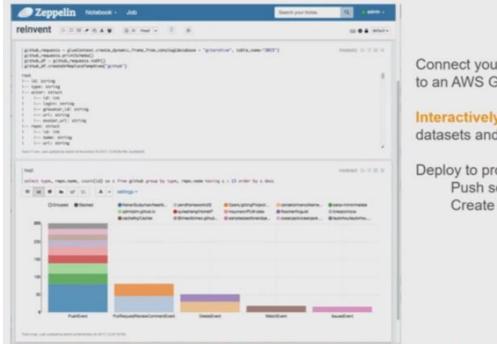
Anatomy of a generated script



This then generates a script for you for this job.



Step 3: Explore and experiment with data



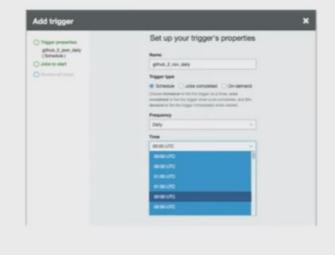
Connect your notebook (e.g. Zeppelin) to an AWS Glue development endpoint.

Interactively experiment and explore datasets and data sources

Deploy to production Push scripts to S3 Create or register with ETL job

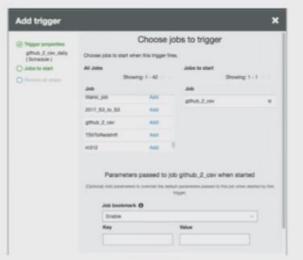


Step 4: Schedule a job



several event types

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pass parameters



Once you have the job registered with Glue, you can trigger the job based on several conditions and event types like using a Cron expression to run it on a schedule, you can also trigger a job based on the completion of another job to make a jobs pipeline, you can also pass parameters to your job triggers to provide some context.

Serverless job execution

No need to provision, configure, or manage servers

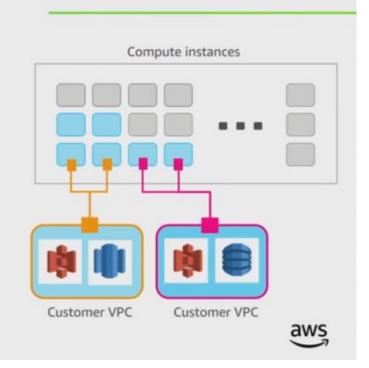
Auto-configure VPC & role-based access security & isolation preserved

Customers can specify job capacity (DPU)

Automatically scale resources

Only pay for the resources you consume per-second billing (10-minute min)





Under the hood: customize AWS Glue scripts

Apache Spark and AWS Glue ETL



SparkSQL AWS Glue ETL

Dataframes Dynamic Frames

Spark core: RDDs

What is Apache Spark?

Parallel, scale-out data processing engine

Fault-tolerance built-in

Flexible interface: Python scripting, SQL

Rich eco-system: ML, Graph, analytics, ...

AWS Glue ETL libraries

Integration: Data Catalog, job orchestration, code-generation, job bookmarks, S3, RDS

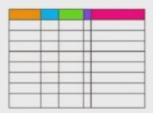
ETL transforms, more connectors & formats

New data structure: Dynamic Frames





Dataframes and Dynamic Frames





Dataframes

Core data structure for SparkSQL

Like structured tables

Need schema up-front Each row has same structure

Suited for SQL-like analytics

Dynamic Frames

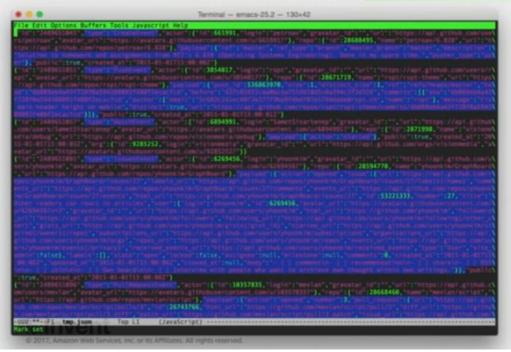
Like dataframes for ETL

Designed for processing **semi-structured** data, e.g. JSON, Avro, Apache logs ...





Public GitHub timeline is ...



semi-structured

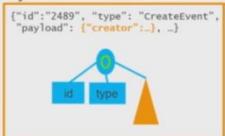
35+ event types

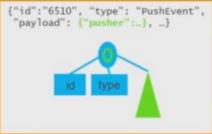
payload structure and size varies by event type

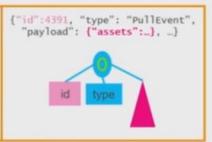


Dynamic Frame internals

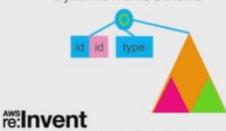
Dynamic Records







Dynamic Frame Schema



schema per-record, no up-front schema needed

Easy to restructure, tag, modify Can be more compact than dataframe rows Many flows can be done in single-pass



Dynamic Frame transforms

15+ transforms out-of-the box

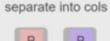
ResolveChoice()





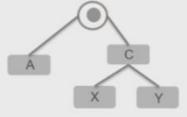








ApplyMapping()





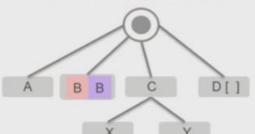




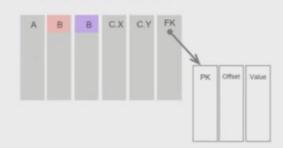


Relationalize() transform

Semi-structured schema



Relational schema



Transforms and adds new columns, types, and tables on-the-fly

Tracks keys and foreign keys across runs

SQL on the relational schema is orders of magnitude faster than JSON processing

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Useful AWS Glue transforms

toDF(): Convert to a Dataframe

Spigot(): Sample data of any Dynamic Frame to S3

Unbox(): Parse string column as given format into Dynamic Frame

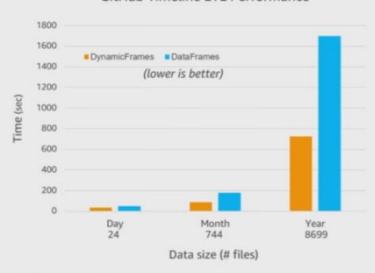
Filter(), Map(): Apply Python UDFs to Dynamic Frames

Join(): Join two Dynamic Frames

And more

Performance: AWS Glue ETL





Configuration 10 DPUs Apache Spark 2.1.1

Workload

JSON to CSV

Filter for Pull events

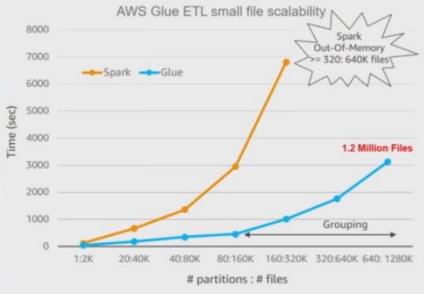
On average: 2x performance improvement



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Performance: Lots of small files



Lots of small files, e.g. Kinesis Firehose

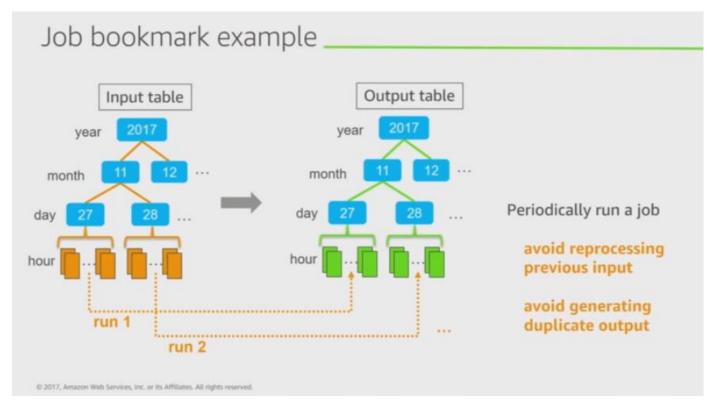
Vanilla Apache Spark (2.1.1) overheads

Must reconstruct partitions (2-pass)

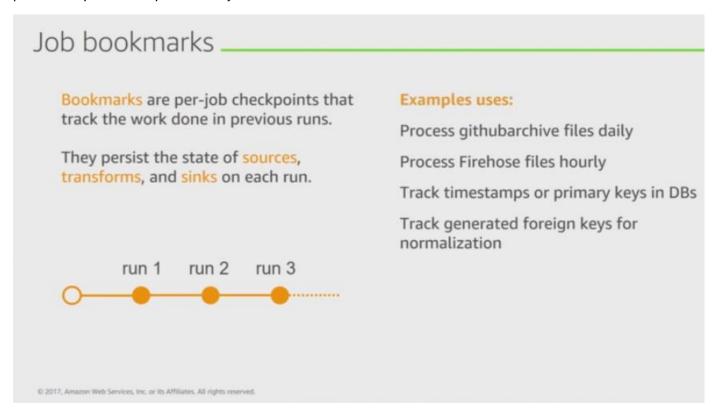
Too many tasks: task per file

Scheduling & memory overheads

AWS Glue Dynamic Frames
Integration with Data Catalog
Automatically group files per task
Rely on crawler statistics

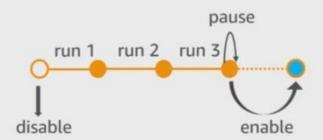


A Job Bookmark lets the script know the last place you stopped processing your data so that the periodic job can start from there the next time and not have to process already processed data. e.g. you don't want to process jobs from the previous day with a daily scheduled job.



Job bookmark options

Option	Behavior			
Enable	Pick up from where you left off			
Disable	Ignore and process the entire dataset every time			
Pause	Temporarily disable advancing the bookmark			



Bookmark state

Examples:

Enable: Process the newest githubarchive partition

Disable: Process the entire githubarchive table

Pause: Process the previous githubarchive partition

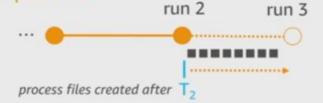
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How do we avoid space blowup?

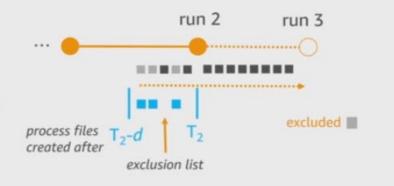
Use timestamps to filter already processed input



Example run 3:

But S3 is eventually consistent?

Maintain exclusion list of files created in *inconsistency window* (size *d*) prior to start.



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4 steps to build a production ETL flow

AWS Glue features

Dynamic frames

Job bookmarks

AWS Glue Announcements

Scala support

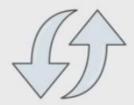
New regions: Asia Pacific (Tokyo) & EU (Ireland)





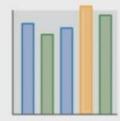
Problem

We were challenged to quickly align extended data and metrics to a Enterprise Software Delivery Management system. One capability of the system is Environment Management, which is used to provide the knowledge regarding environments, what assets make them up and how they align to different software lifecycle efforts. Other capabilities include deployment management, delivery planning and scope management.

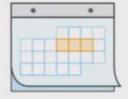


Limited integration with the Enterprise Software Delivery Management System

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BI tools require a data source with application lifecycle context



Major projects require fast alignment to Enterprise Software Delivery Management System





Challenges



Short timeline to produce a data layer.



Resources are not data scientists or ETL developers. Established support does not go beyond

AWS.

2. Crawler updates

schedule, by reading data sources**

Glue Catalog. on

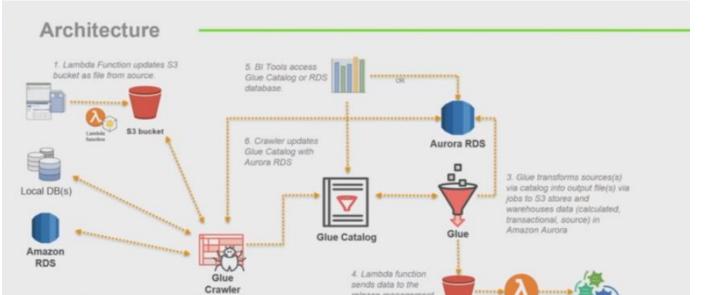
Data is in different spreadsheets or existing databases 10010 01011 10110

aws

Catalog vs. warehousing



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release management

\$3 bucket

system.

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** 25+ different data sources

Value



Leverage existing resources. Glue was quick to learn. No servers means no additional resources to manage, procure or maintain.



Easy to adapt to new data sources and scale availability within short timeframe.



Provided a single source of data (aligned and calculated).

Enabled a scalable data layer/lake



Projects were able to use the data via our Release Management System.





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