

AWS Certified Machine Learning — Speciality Examination (MLS-C01)

Curriculam

- Data Engineering (20%)
- Exploratory Data Analysis (24%)
- Modeling (36%)
- Implementation and Operations (20%)

Data Engineering

- Storage Solutions
 - S3 Data Lakes
 - DynamoDB
- Transformation
 - Glue
 - Glue ETL

Data Engineering

- Streaming
 - Kinesis
 - Kinesis Video Streams
- Workflow Management Tools
 - Data Piplelines
 - AWS Batch
 - Step Functions

Exploratory Data Analysis

- Data Science
 - scikit-learn
 - Data Distributions
 - Trends and Seasonality
- Analysis Tools
 - Athena
 - _ Quicksight
 - Elastic Map Reduce (EMR)
 - Apache Spark

Exploratory Data Analysis

- Feature Engineering
 - Imputation methods
 - Outliers
 - Binning/Categorizing Data
 - Log transforms
 - One-hot encoding
 - Scaling and Normalization

Modeling

- Deep Learning
 - Multi-layer Perceptrons (MLPs)
 - Convolutional Neural Networks (CNNs)
 - Recurrent Neural Networks (RNNs)
 - ANN Tuning and Regularization Techniques
- SageMaker
 - Architecture
 - Built-in Algorithms
 - Automatic Model Tuning
 - SageMaker Integration with other services Spark

Modeling

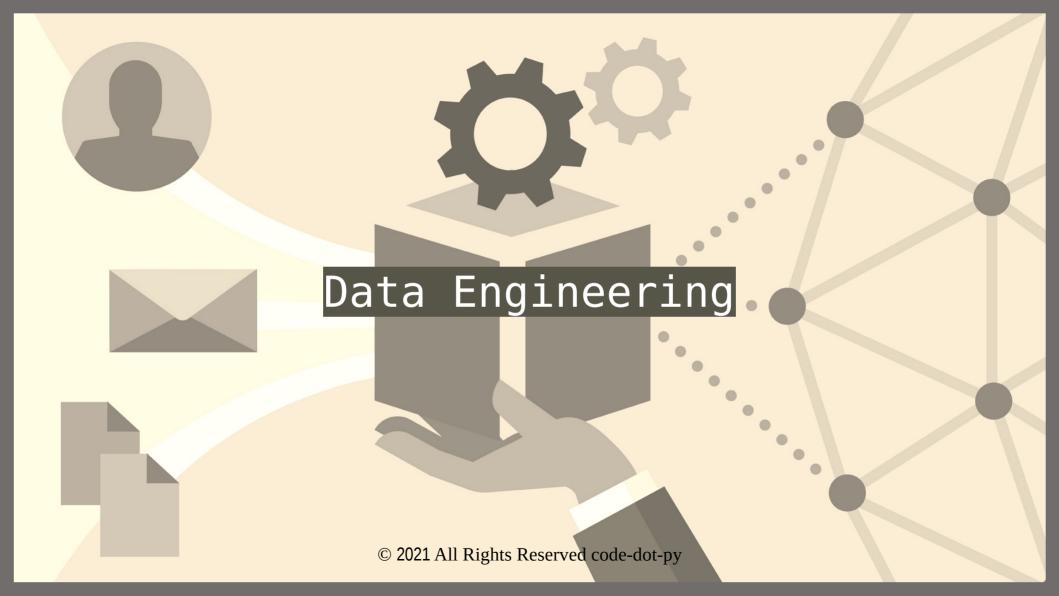
- High-level AI Services
 - Comprehend
 - Translate
 - Polly
 - Transcribe

 - Rekognition
 - Additional Services Personalize, Forecast, Textract etc
 - DeepLens
- **Evaluating and Tuning**
 - Confusion Matrix
 - RMSE
 - Precision and Recall
 - F1 Score
 - ROC / AUC

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Implementation and Operations

- Sagemaker Operations
 - Using containers
 - Security with SageMaker
 - Choosing instance types
 - A/B testing
 - Tensorflow integration
 - SageMaker Neo and GreenGrass
 - SageMaker Pipes
 - Elastic Inference
 - Inference Pipelines



AWS S3 Overview

- S3 allows for storing objects (files) in buckets (directories)
- Buckets must have a globally unique name
- The full path of the objects is called 'Key'. Example:
 - <bucketname>/<filename>.txt
 - --<bucketname>/<foldername>/<filename>.txt
- The maximum object size that can be stored: 5TB

AWS S3 for Machine Learning

- Backbone for many AWS ML services (Ex: SageMaker)
- Core service for Data Lake
 - Infinite size, no provisioning
 - 99.99999999% durability
 - S3 allows for decoupling (segregating) storage for all the compute based services. Examples:
 - EC2, Athena, Redshift, Rekognition, Glue
- Centralized Architecture all the data at the same place
- Object Storage supports any file format
- Common formats for ML CSV, JSON, Parquet, ORC, Avro, Protobuf

AWS S3 Data Partitioning

- Pattern for speeding up range queries (Eg: AWS Athena)
- Partitioning Examples:
 - By Date: s3://<bucketname>/<dataset>/year/month/day/hour/<datafile>.csv
 - By Product: s3://<bucketname>/<dataset>/product-id/<datafile>.csv
- We should choose the partitioning type based on use case
- Some tools like Kinesis and Glue can help with partitioning

AWS S3 Storage Tiers

- Amazon S3 Standard General Purpose (GP)
- Amazon S3 Standard Infrequent Access (IA)
- Amazon S3 One Zone-Infrequent Access
 - Cheaper IA with diluted availability
- Amazon S3 Intelligent Tiering
 - New Amazon determines where to put data to save cost
- Amazon Glacier
 - Archival

AWS S3 Storage Tiers

	Standard	Standard - Infrequent Access	One - Infrequent Access	S3 Intelligent- Tiering	Glacier
Durability	99.999999999%	99.999999999%	99.99999999%	99.999999999%	99.99999999%
Availability	99.99%	99.9%	99.5%	99.90%	NA
AZ	≥3	≥3	1	≥3	≥3
Concurrent facility fault tolerance	2	2	0	1	1

Frequently accessed Infrequently accessed Intelligent (new!) Archives

S3 Lifecycle Rules

- In order to save on cost, the lifecycle rules help in moving data between different tiers
- Example:
 - General Purpose (GP) -> Infrequent Access (IA) -> Glacier
- Transition actions Objects are transitioned to another storage class
 - Move objects from:
 - GP to IA, 60 days post creation
 - IA to Glacier 6 months post creation
- Expiration actions S3 deletes expired objects on our behalf
 - Log files can be set to delete after a specific period of time

S3 Security - Encryption for Objects

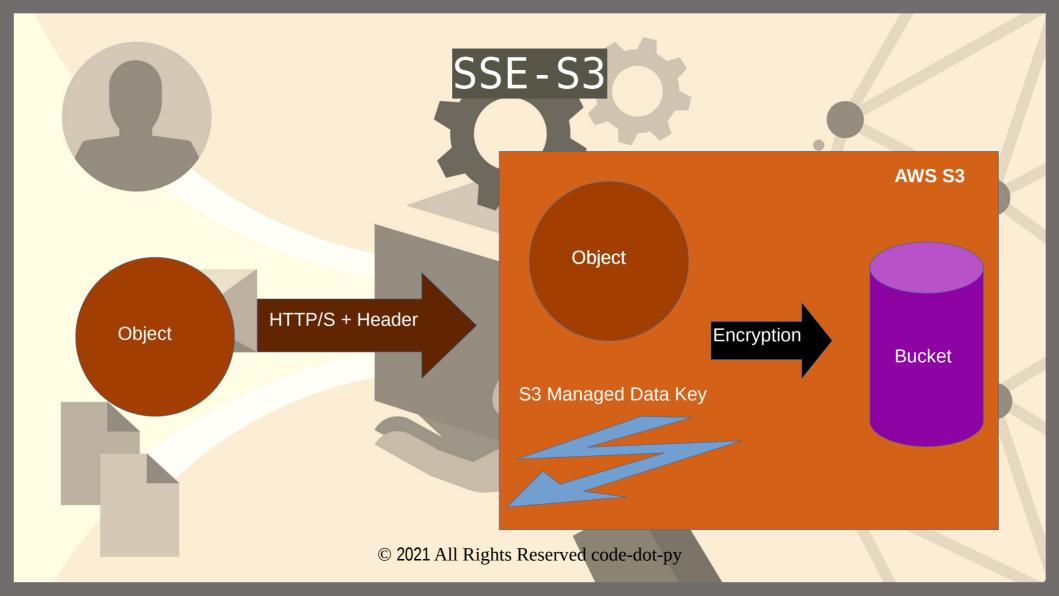
• There are four methods of encrypting objects in S3:

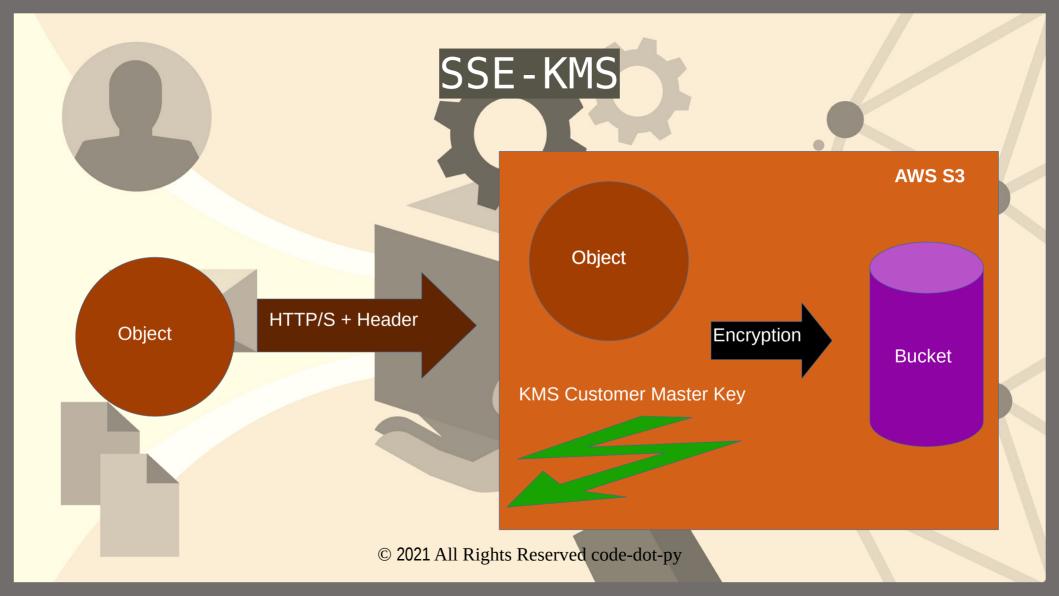
- SSE-S3: Encrypts S3 objects using keys handled and managed by AWS
- SSE-KMS: Use AWS key Management Service to manage encryption keys
 - Additional Security
 - Audit trail for KMS key usage

S3 Security - Encryption for Objects

- SSE-C: We need to use our own encryption keys
- Client Side Encryption

 From an ML perspective, SSE-S3 and SSE-KMS will be the most likely used scenarios





S3 Security

- User Based
 - IAM Policies which API calls the user should be allowed
- Resource Based
 - Bucket Policy allowing cross account access
 - Object Access Control List (ACL) more precise control
 - Bucket Access Control List (ACL) less commonly used

S3 Bucket Policies

- JSON based policies
 - Resources: buckets and objects
 - Actions: Set of API to Allow or Deny
 - Effect: Allow / Deny
 - Principal: The account or user to apply the policy to

S3 Bucket Policies

- Use S3 bucket policies for:
 - Granting public access to the bucket
 - For objects to be encrypted at upload
 - Grant access to another account (Cross Account)

S3 Security — Points to Remember

- Networking VPC Endpoint Gateway
 - Allow traffic to stay within your VPC
 - Make sure the private services (Eg: SageMaker) can access S3
- Logging and Audit:
 - S3 access logs can be stored in other S3 bucket
 - API calls can be logged in AWS CloudTrail
- Tagged Based (combined with IAM and bucket policies)

AWS Kinesis - Overview

- Kinesis is a managed alternative to Apache Kafka
- Great for application logs, metrics, IoT, click streams etc
- Any reference to 'real-time' in the exam is an indication of relation to Kinesis
- Great for streaming processing frameworks (Spark, NiFi etc)
- Data is automatically replicated synchronously to 3 AZs

AWS Kinesis — Key Services

- Kinesis Streams low latency streaming ingest
 at scale
- Kinesis Analytics perform real-time analytics on streams using SQL
- Kinesis Firehose load streams into S3, Redshift, ElastiSearch and Splunk
- Kinesis Video Streams meant for streaming video in real-time

AWS Kinesis — Architecture

Click streams

loT devices

Metrics & Logs Kinesis

Streams

AWS Kinesis

> Kinesis Analytics

Kinesis

Firehose

Amazon S3 Bucket

> Amazon Redshift

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Kinesis Streams - Overview

Streams are divided into ordered Shards / Partitions

PRODUCERS

SHARD 2

CONSUMERS

SHARD 3

Shards have to be provisioned in advance (capacity planning)

Kinesis Streams - Overview

- Data retention is 24 hours by default and can go upto 7 days
- Ability to reprocess/replay data
- Multiple applications can consume the same stream
- Once data is inserted in Kinesis, it cannot be deleted (data immutability)
- Records can be upto 1 MB in size fine for streaming use cases but not for large data analysis

Kinesis Data Streams - Limits

- Producers:
 - 1MB/s or 1000 messages/s write speed per shard
 - If exceeded 'ProvisionedThroughputException'
- Consumer (Classic):
 - 2MB/s read speed per shard across all consumers
 - --Max 5 API calls/s/shard across all consumers
- Data Retention:
 - By default 24 hours
 - Can be extended to upto 7 days

Kinesis Data Firehose

- Fully managed service, no administration
- Near real time (60 seconds latency minm for non full batches)
- Can perform data injestion into the following four services:
 - Redshift
 - Amazon S3
 - ElasticSearch
 - Splunk
- Automatic scaling

Kinesis Data Firehose

- Supports many data formats
- Data conversion from CSV/JSON to Parquet/ORC (only for S3)
- Data transformation through AWS Lambda (CSV => JSON)
- Supports compression when target is Amazon S3 (GZIP, ZIP and SNAPPY)
- Pay for the amount of data going through Firehose

Kinesis Data Firehose - Diagram

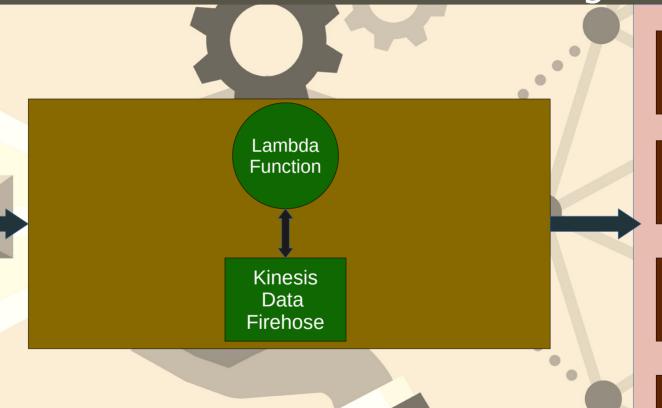
Kinesis Producer Library

Kinesis Agent

Kinesis Data Streams

Cloudwatch Logs and Events

> IoT Rule Actions



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Amazon S3

Redshift

Elsatic

Search

Splunk

Kinesis Data Streams vs Firehose

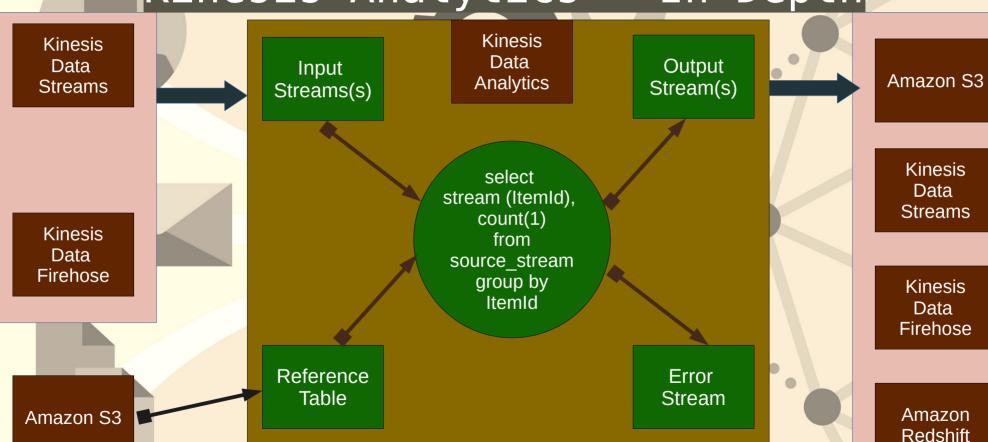
Streams

- Supports custom code writing for producer/consumer
- Real-time applications (latency ~200ms for classic and ~70ms for enhanced fan-out)
- Must manage scaling ourselves (shard splitting/merging)
- Data Storage for 1 to 7 days, replay capability, multi consumers

Kinesis Data Streams vs Firehose

- Firehose
 - Deliver or ingestion service
 - Fully managed. Can send to S3, Splunk, Redshift, ElasticSearch
 - Serverless data transformations with Lambda
 - Near real time (lowest buffer time is 60 seconds)
 - Automated scaling
 - No data storage no replay capability

Kinesis Analytics — In Depth



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Kinesis Data Analytics — Use Cases

- Streaming ETL
 - select columns, make simple transformation on streaming data
- Real-time metric generation
 - live leaderboard for a mobile game
- Responsive analytics
 - look for certain criteria and build alerting

Kinesis Data Analytics - Features

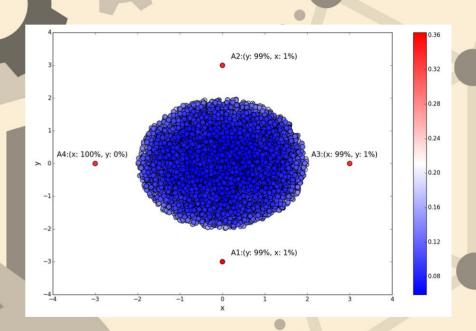
- Pay only for the resources consumed not cheap
- Serverless and scales automatically
- Use IAM permissions to access streaming source and destination(s)
- SQL or Flink to write the computations
- Schema discovery
- Lambda can be used for preprocessing

Machine Learning on Kinesis Data Analytics

- There are two algorithms that can be used:
 - Random Cut Forest
 - Hotspots

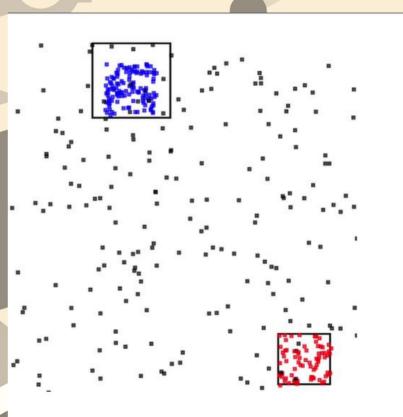
ML on Kinesis Data Analytics

- Random Cut Forest
 - Used for anamoly
 detection in a
 - numerical column data
 - in a stream
 - Provided as a SQL like function to use
 - Uses recent history to compute the model



ML on Kinesis Data Analytics

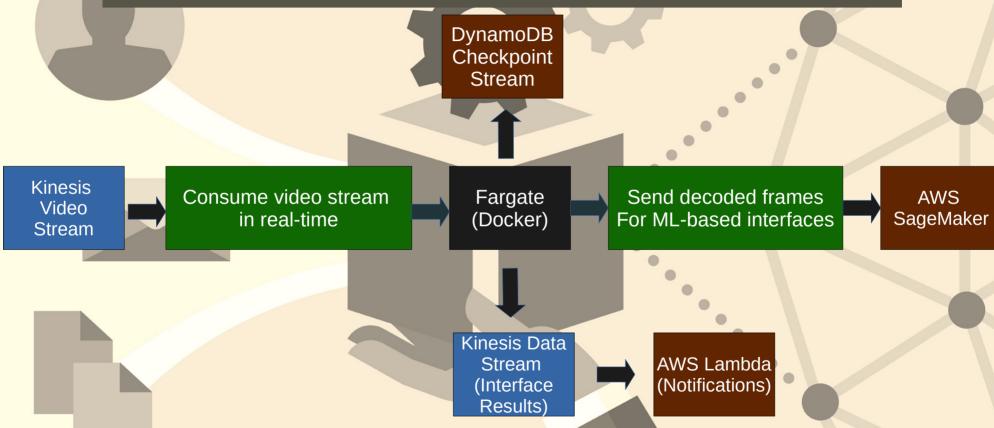
- Hotspot
 - Locate and return information about relatively
 - dense regions in the data
 - Provided as a SQL like
 - function to use



Kinesis Video Stream

- Producers
 - Cameras security, body-worn, action, smartphone
 - AWS DeepLens
 - Audio and Image feeds
 - RADAR data
 - One producer per video stream
- Consumers
 - Custom MXNet, Tensorflow
 - AWS SageMaker
 - Amazon Rekognition Video
- Data can be retained for 1 hour to upto 10 years
- Video playback capability

Kinesis Video Stream — Use Case



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Kinesis Summary

- Kinesis Data Stream read real-time data and create real-time ML applications on top
- Kinesis Data Firehose ingest massive data with near-real-time scenario
- Kinesis Data Analytics real-time ETL/ML algorithms on stream
- Kinesis Video Stream real-time video stream to create ML applications

AWS Glue

- Glue Data Catalog
 - Metadata repository for all the tables within the account
 - Automated Schema Inferences
 - Schema Versioning
 - Integrates with AWS Athena or redshift Spectrum (schema and data discovery)
 - 'Glue Crawlers' can help building the Glue Data Catelog

AWS Glue

- Glue Data Catelog Crawlers
 - Crawlers go through the data to infer schemas and partitions
 - They work with JSON, Parquet, CSV, Relational data etc
 - They work with services like AWS S3, Redshift, RDS
 - Crawlers can be run on a schedule or on-demand
 - Need IAM role/credentials to access the data stores

AWS Glue and S3 Partitions

- Glue crawler will extract partitions based on how the S3 data is organized
- It has to be thought-of upfront as to how the data will be queried
- Example:

mysam<mark>plem</mark>ltestbucket

- A device is sending sensor data every hour
- Query primarily by time-range -> Organize the bucket like:
 - s3://my-bucket/dataset/yyyy/mm/dd/device
- Query primarily by device -> Organize the bucket like:
 - s3://my-bucket/dataset/device/yyyy/mm/dd/

AWS Glue ETL

- Extract, Transform and Load
- Transform Data, Clean Data, Enrich Data before performing any analysis
- Glue ETL Features:
 - Generate ETL code in Python or Scala, the code can also be updated/modified
 - Can also work with custom Spark or PySpark scripts
 - Targets can be S3, JDBC (RDS, Redshift etc) or in Glue Data Catalog
- Fully managed, cost effective pay only for the resources consumed
- Jobs are executed on a serverless Spark platform
- Glue Scheduler to schedule the jobs
- Glue Triggers to automate job runs based on 'events'

AWS Glue ETL - Transformations

- Bundled Transformations:
 - DropFields, DropNullFields remove (null) fields
 - Filter -specify a function to filter records
 - Join to enrich data
 - Map add fields, delete fields, perform external lookups
- Machine Learning Transformations:
 - FindMatches ML: Identify duplicate or matching records in your dataset, even when the records do not have a common unique identifier and no fields match exactly. Useful for data de-duplication
- Format conversions: CSV, JSON, Avro, Parquet, ORC, XML
- Apache Spark Transformations (Eg: k-means)

AWS Data Store for Machine Learning

- Redshift
 - Data Warehousing, SQL Analytics, OLAP
 - Load data from S3 to Redshift
 - Use Redshift Spectrum to query data directly in S3
- RDS, Aurora
 - Relational Store, SQL, OLTP
 - Must provision servers in advance

AWS Data Store for Machine Learning

- DynamoDB
 - NoSQL data store
 - Serverless provision read/write capacity
 - Useful to store a machine learning model served by your application
- S3
 - Object storage
 - Serverless, infinite storage
 - Integration with most AWS Services

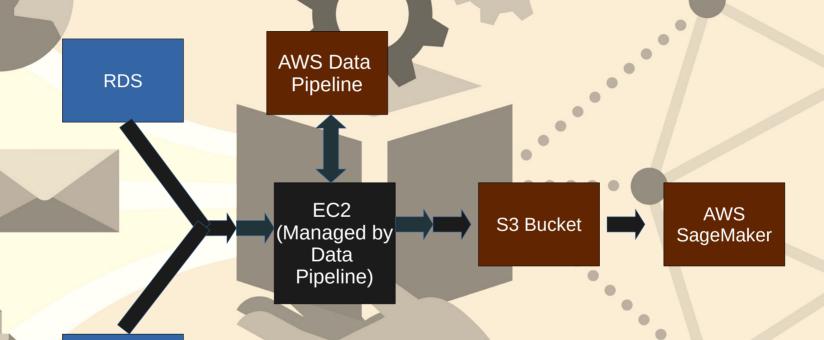
AWS Data Store for Machine Learning

- ElasticSearch
 - Indexing of data
 - Search amongst data points
 - Clickstream Analytics
- ElastiCache
 - Caching mechanism
 - Not really used for Machine Learning

AWS Data Pipeline Features

- Destinations include S3, RDS, DynamoDB,
 Redshift, EMR
- Manages task dependencies
- Retries and notifies on failures
- Data source may be on-premise
- Highly available

AWS Data Pipeline Example



DynamoDB

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AWS Data Pipeline vs Glue

• Glue:

- Glue ETL: Runs ApacheSpark Code
- Scala or Python based
- Focused on ETL
- Not focused on configuring or managing resources
- Catalogs data for Athena or Redshift Spectrum

Data Pipeline:

- Orchestration service
- More control over:
 - The environment
 - Compute resources that run the code
 - Code itself
- Allows access to EC2 or EMR instances
- Creates resources in same account

AWS Batch

- Run batch jobs as Docker images
- Dynamic provisioning of the instances (EC2 and Spot Instances)
- Optimal quantity and type based on the volume and requirements
- No need to manage clusters, fully serverless
- Just pay for the underlying EC2 instances
- Schedule batch jobs using CloudWatch Events
- Orchestrate Batch Jobs using AWS Step Functions

AWS Batch vs Glue

• Glue:

- Glue ETL: Runs Apache
 Spark Code
- Scala or Python based
- Focused on ETL
- Not focused on configuring or managing resources
- Catalogs data for Athena or Redshift Spectrum

Batch:

- For any computing job regardless of the job
- Must be provided with a Docker image
- The resources are created within the account and managed by Batch
- For a non-ETL requirement,
 Batch is a better option

AWS DMS — Database Migration Service

- Quickly and securely migrate databases to AWS
- Resilient and self-healing
- The source database remains available during the migration
- Supports:
 - Homogeneous migrations Oracle to Oracle
 - --Hetrogeneous migrations SQL Server to Aurora
- Continuous Data Replication using CDC
- An EC2 instance is needed to perform the replication task

AWS DMS vs Glue

• Glue:

- Glue ETL: Runs Apache
 Spark Code
- Scala or Python based
- Focused on ETL
- Not focused on configuring or managing resources
- Catalogs data for Athena or Redshift Spectrum

DMS:

- Continuous Data Replication
- Service for Database migration
- No data transformation
- Post migration, ETL can be performed

AWS Step Functions

- Used to orchestrate and design workflows
- Easy visualizations
- Advanced Error Handling and Retry mechanism outside the code
- Audit of the history of workflows
- Ability to 'Wait' for an arbitary amount of time
- Maximum execution time of the state machine is 1 year

Step Functions — Examples Train a Machine Learning Model

```
"StartAt": "Generate dataset",
  "States": {
   "Generate dataset": {
     "Resource": "<GENERATE_LAMBDA_FUNCTION_ARN>",
                                                                                                     Start
     "Type": "Task".
     "Next": "Train model (XGBoost)"
                                                                                                Generate dataset
    "Train model (XGBoost)": [
      "Resource": "arn:
<PARTITION>:states:::sagemaker:createTrainingJob.sync",
                                                                                             Train model (XGBoost)
      "Parameters": {
        "AlgorithmSpecification": {
          "TrainingImage": "<SAGEMAKER_TRAINING_IMAGE>",
                                                                                                  Save Model
          "TrainingInputMode": "File"
        "OutputDataConfig": {
                                                                                                Batch transform
          "S30utputPath": "s3://<S3_BUCKET>/models"
        "StoppingCondition": {
                                                                                                      End
          "MaxRuntimeInSeconds": 86400
        "ResourceConfig": {
          "InstanceCount": 1,
          "InstanceType": "ml.m4.xlarge",
```

Step Functions — Examples Tune a Machine Learning Model

```
"StartAt": "Generate Training Dataset".
   "States": {
                                                                                                    Start
       "Generate Training Dataset": {
            "Resource": "<GENERATE_LAMBDA_FUNCTION_ARN>".
                                                                                           Generate Training Dataset
            "Type": "Task".
            "Next": "HyperparameterTuning (XGBoost)"
                                                                             \odot
                                                                                        HyperparameterTuning (XGBoost)
        "HyperparameterTuning (XGBoost)": {
           "Resource": "arn:
<PARTITION>:states:::sagemaker:createHyperParameterTuningJob.sync".
                                                                                              Extract Model Path
            "Parameters": {
                "HyperParameterTuninaJobName.$": "
<JOB_NAME_FROM_LAMBDA>".
                                                                                       HyperparameterTuning - Save Model
                "HyperParameterTuningJobConfig": {
                    "Strateay": "Bayesian".
                    "HyperParameterTuningJobObjective": {
                                                                                              Extract Model Name
                        "Type": "Minimize",
                        "MetricName": "validation:rmse"
                                                                                               Batch transform
                    "ResourceLimits": {
                        "MaxNumberOfTrainingJobs": 2,
                        "MaxParallelTrainingJobs": 2
                                                                                                    End
                    "ParameterRanges": {
                                      © ZUZI All Rights Reserved code-dot-py
```

Step Functions — Examples Manage a Batch Job

```
"Comment": "An example of the Amazon States Language for
notification on an AWS Batch job completion",
 "StartAt": "Submit Batch Job",
 "TimeoutSeconds": 3600,
 "States": {
   "Submit Batch Job": {
     "Type": "Task",
     "Resource": "arn:<PARTITION>:states:::batch:submitJob.sync",
     "Parameters": {
       "JobName": "BatchJobNotification",
       "JobQueue": "<BATCH_QUEUE_ARN>",
       "JobDefinition": "<BATCH_JOB_DEFINITION_ARN>"
     "Next": "Notify Success",
     "Catch": [
         "ErrorEquals": [ "States.ALL" ],
         "Next": "Notify Failure"
   "Notify Success": {
     "Type": "Task",
     "Resource": "arn:<PARTITION>:states:::sns:publish",
```

