

US Healthcare Price Transparency in Coverage

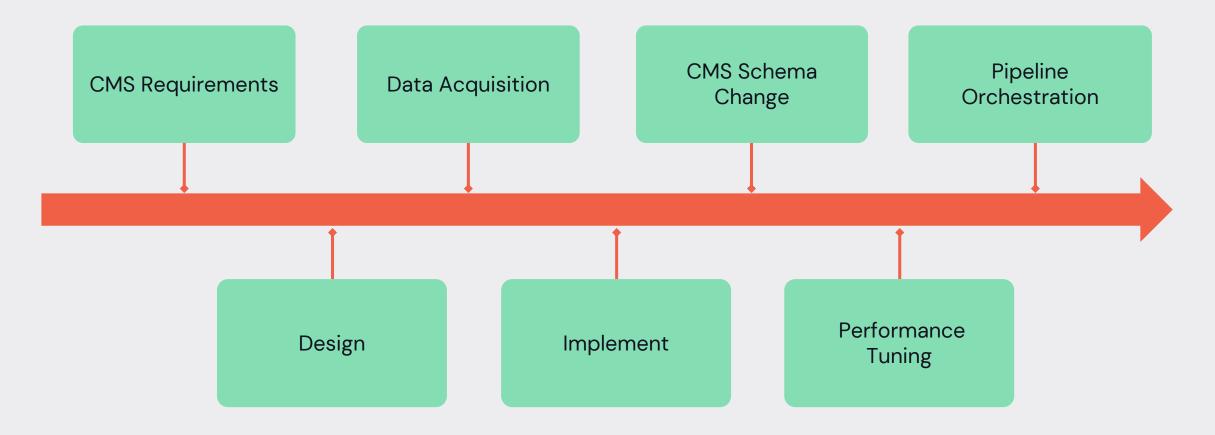
Utilizing Databricks and Delta Lake

ORGANIZED BY 😂 databricks

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Journey

A tale of Linear and Horizontal Progression





Who are we?

About us

- A global health services company with the mission of improving the health, well-being, and peace of mind of those we serve by making health care simple, affordable, and predictable.
 - easy to get care letting you choose how, when, and where you want it.
 - A more affordable health care by partnering with providers who provide quality, cost-effective care.
 - A comprehensive health care coverage with "no surprises."



cigna.com/about-us/



What is Price Transparency?

Phase One - Machine Readable Files (MRF)

Requirements

- CMS mandated¹ all health insurance payers publicly post MRF files with contracted provider rates for all procedure codes.
- 3 Types of files:
 - In-Network Contracted Rates
 - Out-of Network Allowed Amounts
 - Table Of Contents
- MRF schema set by CMS².

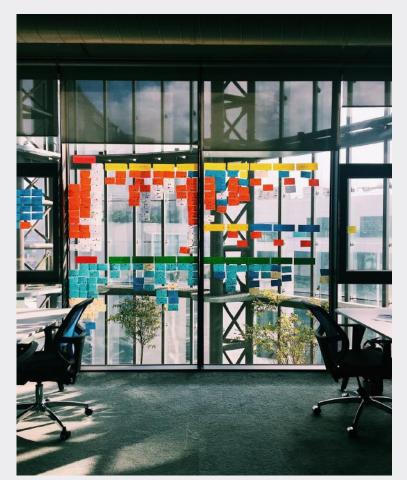


Photo by <u>Irfan Simsar</u> on Unsplash

Price Transparency

Phase One - Machine Readable Files (MRF)

Requirements – contd...

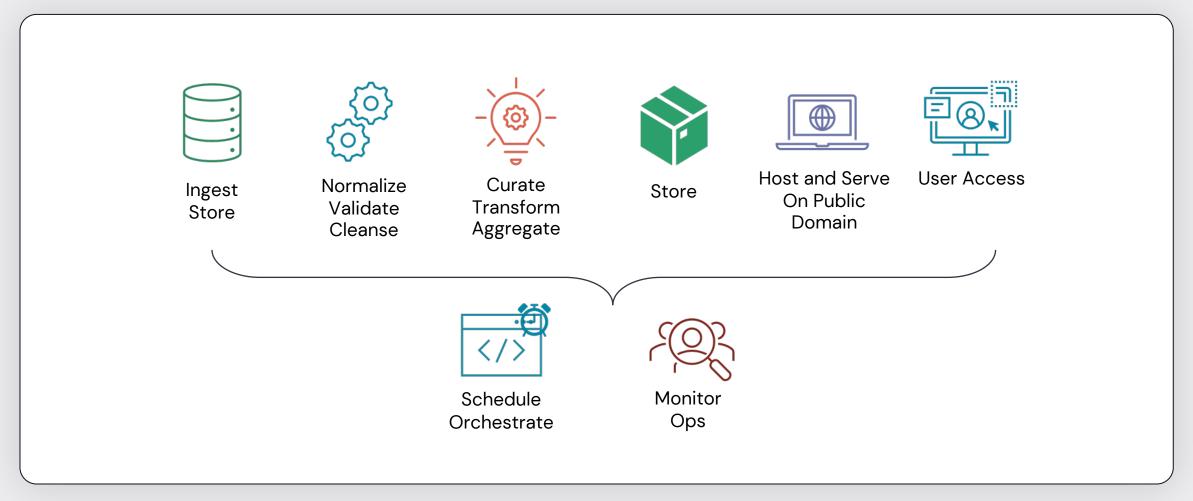
- JSON files, one for each plan¹
- Generated monthly
- Hosted on public domain
- Include data from partners

36	<pre>"negotiated_rates": [{</pre>
37	"provider_groups": [{
38	"npi": [111111111, 222222222, 3333333333, 444444444,
39	"tin":{
40	"type": "ein",
41	"value": "11-111111"
42	}
43	},{
44	"npi": [111111111, 222222222, 3333333333, 444444444,
45	"tin":{
46	"type": "ein",
47	"value": "22-222222"
48	}
49	}],
50	<pre>"negotiated_prices": [{</pre>
51	<pre>"negotiated_type": "negotiated",</pre>
52	"negotiated_rate": 123.45,
53	"expiration_date": "2022-01-01",
54	"service_code": ["18", "19", "11"],
55	"billing_class": "professional",
56	"billing_code_modifier": ["AS"]
57	}. {



10,000 Foot View

Data Flow



The Data

The power of scalability



Photo by benjamin lehman on Unsplash



Thousands of Providers

$\cdot \bullet \cdot$

Tens of Thousands of Billing Codes

CPT | ICD 10



Hundreds of Plans



Billions of records



More than 60TB of Data

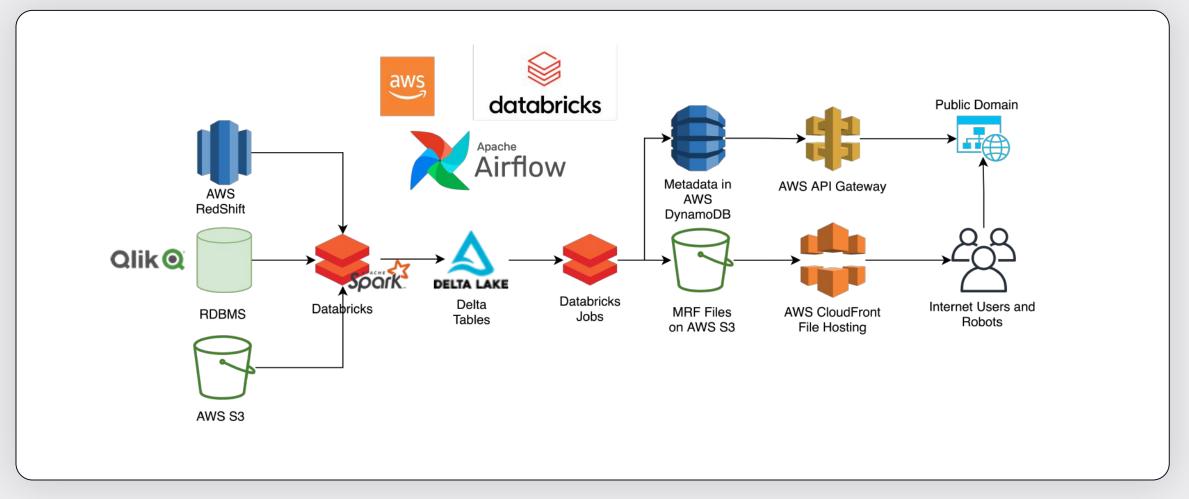


Let's dig in



Components

Using Databricks on AWS



Databricks Components

Spark to the rescue

Code

- Scala / Python / Bash
- Notebooks
- Packaged whl's & jar's

CICD / Infrastructure

- REST API and Terraform
 - Cluster orchestration
 - Policy enforcement
 - Job runs (via Airflow)
- Docker image with Databricks CLIs for integration testing
- Automated customer onboarding and provisioning.

Apache Spark

- Dataset/frame APIs (Scala)
- pySpark
- Used for :
 - Normalization
 - Validation
 - Cleansing
 - Aggregation
 - Joins

instance pools

to 8xlarge

/clusters/*

compliance

Nitro instances for HIPAA

Instance types for storage

and memory optimized

nodes from i3en.xlarge to

24xlarge and r5dn.xlarge

Latest runtimes 10.x

Auto-provisioned

- Glue catalog integration
- S3 based logging destination
- Init scripts to auto-tag EC2 instances for FinOps
- T-Shirt sizing for widerange of capacity requirements.

/jobs/*

- Python WHL
- Scala JAR
- Notebooks
- Service Principals and Managed cluster and Job permissions

/policies/clusters/*

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Automation with Databricks API

😂 databricks

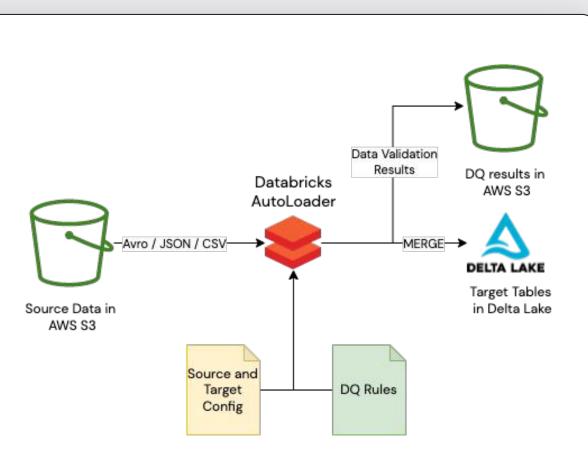
Delta Lake



Reusable Notebooks

Based on Databricks Autoloader

- Autoloader in Directory Listing Mode
- Data Validation Rules and Reporting
- DeltaLake MERGE to target
- Current and History View of Data
- Filters and Additional Columns using in-built UDFs
- Registers tables to Glue Catalog



Data Storage and Processing

Why Delta Lake?

- Scales well for billions of records
- MERGE capabilities to maintain current view
- Great for sharing data with other teams
- Enables streaming use cases to process CDC data from sources and from DeltaLake using Change Data Feed
- Intermediary results of aggregations and joins improving performance
- Manual & Auto-optimization, Z-ORDERing for improved performance
- Makes reporting and metrics faster with its metadata capabilities

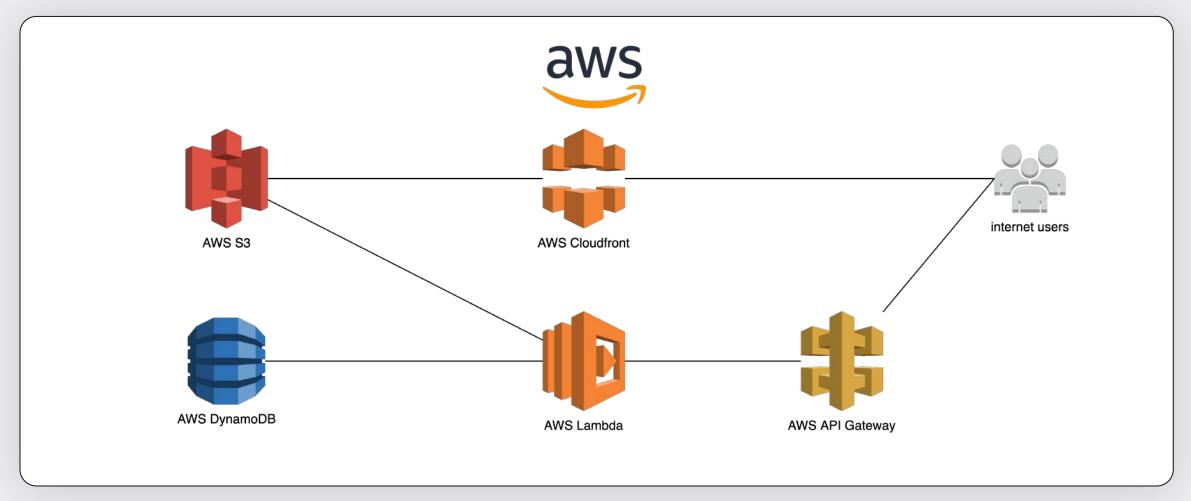


Serving Layer



Solution Architecture

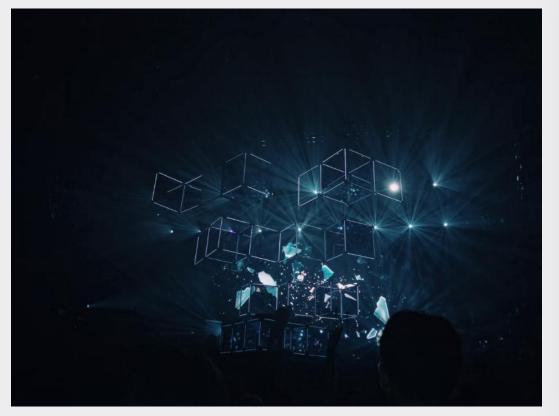
AWS & Other



Performance Tuning



With Apache Spark & Delta Lake



Techniques

- Pre-partitioning sources on lowcardinality fields
- Z-Ordering
- Delta Lake Optimize
- Window Functions
- Aggregators
- Choosing the right EC2 instance types





General Best Practices

What we tried

- - using all Datasets (strictly typed)
- more shuffle partitions (smaller task chunks to avoid OOM)
- removing distincts (replaced with window functions to avoid a second shuffle)
- using delta format for initial write out (delta cache boost)
- breaking the job up into smallest possible steps



Photo by Kolleen Gladden on Unsplash

Aggregators

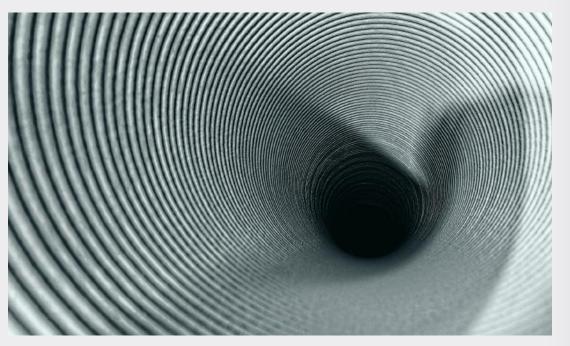


Photo by Ricardo Gomez Angel on Unsplash

Aggregator[-IN, BUF, OUT]

- *IN* The input type for the aggregation.
- **BUF** The type of the intermediate value of the reduction.
- **OUT** The type of the final output result.

• Strictly typed datasets



Window Functions

WindowSpec

- Can be more efficient than traditional group by, assuming you pre-partition data based on the same id (one shuffle only)
- You don't lose any extraneous columns as you would with a traditional group by

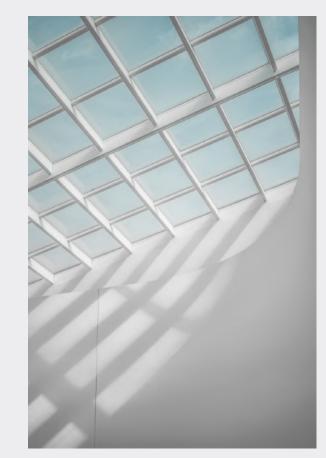


Photo by Jayden So on Unsplash



Window Function Example

Code snippets

- 1 // Define a window and some helper functions
- 2 val proceedure_window: WindowSpec = Window.partitionBy(col("procedure"))
 - .orderBy(col("procedure"))
- 4 def selectTopOneRecord(window: WindowSpec)(df: DataFrame): Dataset[Row] = {
 - df.withColumn("row_number", row_number().over(window))

```
.filter(col("row_number") === 1)
```

```
.drop("row_number")
```

```
8 }
```

3

5

6

7

9 def addSetColumn(structCol: String, window: WindowSpec): Column = {

```
10 collect_set(structCol).over(window)
```

Window Function Example

Code snippets

- 1 // Transform a data set
- 2 case class RawData(id:Long,name:String,proceedure:String,cost:Double)
- 3 case class Provider(id:Long,name:String,cost:Double)
- 4 case class ProcedureWithProviderList(proceedure:String,providers:Seq[Provider])
- 5 def addProdcureStruct(): Column = { struct(col("id"), col("name"), col("cost"))}
- 6 val my_transformed_ds = my_input_ds
 - .withColumn("procedures", addProdcureStruct())
 - .withColumn("procedures",addSetColumn("procedures",procedure_window))
 - .transform(selectTopOneRecord(procedure_window))
 - .as[ProcedureWithProviderList]

7

8

9

10

Issue #1

Even Spark has its limits

CMS In-network rates MRF Schema is not Spark friendly

- Expected file size about 1.6 TB uncompressed and 700 GB compressed.
- Aggregate 1000's of billing codes & more than 2GB of data into an Array column
- Aggregation action forces Spark to pull all partitioned data to the same executor.

java.lang.IllegalArgumentException: Cannot grow BufferHolder by size XXXXXXXX because the size after growing exceeds size limitation 2147483632

Solution

Back to basics

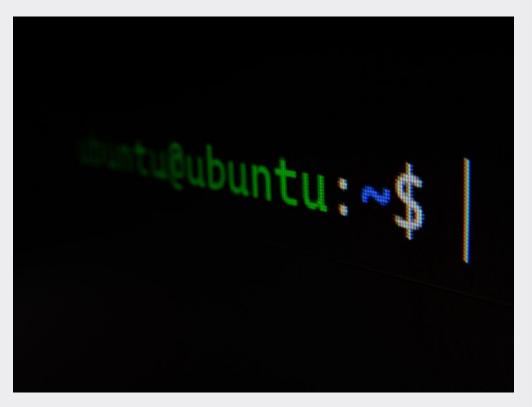


Photo by Gabriel Heinzer on Unsplash

Using Databricks as a compute platform

- It's a linux box under the hood!
 - Scalable EC2*
- Notebooks make it easy to mix in OS commands (%sh) with Scala or Python based Spark code
- Mount storage from AWS S3*

* when using Databricks on AWS



Solution

Back to basics

Using Databricks as a compute platform

- Reading JSON data written out from Spark
- Using storage optimized instances
- Stitching together JSON data with bash (%sh) commands in a notebook
- Utilizing Databricks mount points to read / write data
- Monitoring server metrics with Ganglia UI

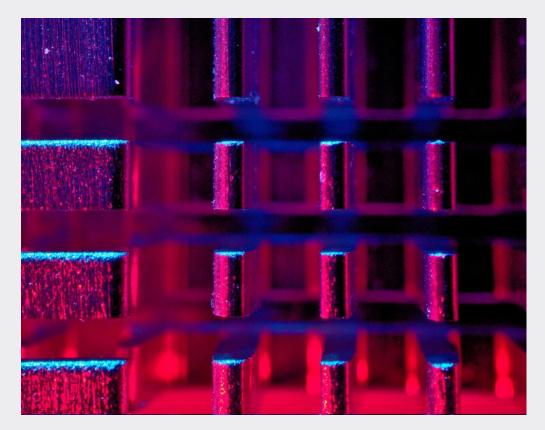


Photo by Michael Dziedzic on Unsplash



Issue #2

Serving up a large amount of data for a public domain

- Terabytes of data over HTTP
- Products with expected file sizes of 1.6 TB for a single JSON file.
- Public access
- 1-[n] downloads for each file



Photo by Timon Studler on Unsplash

Solution

Serving up a large amount of data for a public domain

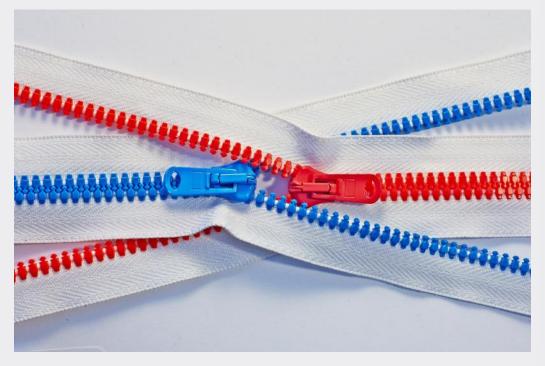


Photo by Tomas Sobek on Unsplash

- Compressing data during Spark write and file stitching process
- Using window functions to remove duplicate rows
- Utilizing AWS CloudFront to cache data for downloads



Automation



DevOps

Automate end-to-end pipelines and runtime



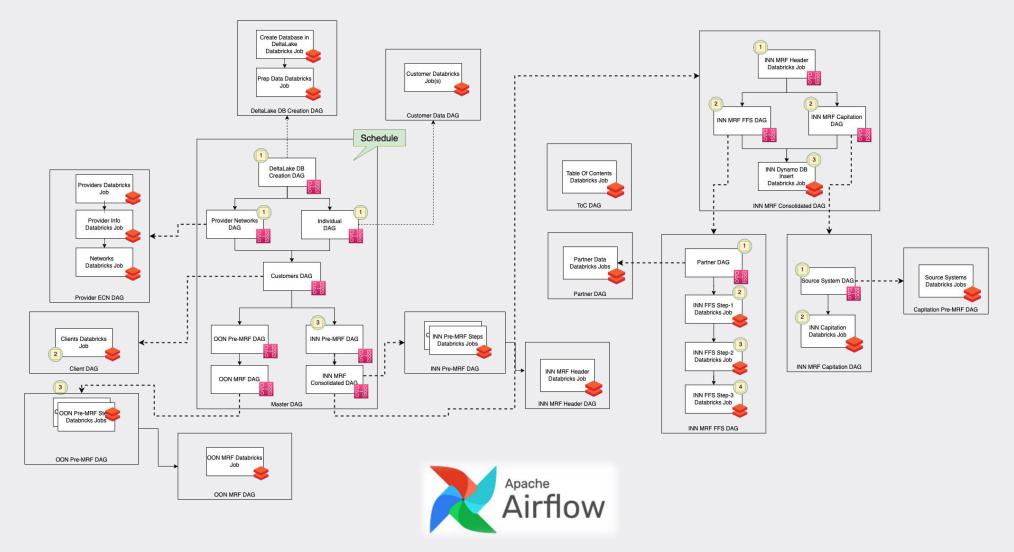
Photo by Christophe Dion on Unsplash

Curation-D

- Automated pipeline
 - Databricks Jobs
 - Jenkins
 - Terraform
 - SBT / Plz
- Airflow for Scheduling and Orchestration



Master DAG





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Thank you

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Appendix

Disclaimer

• All architectural & code samples are for demonstrative purposes only and should not be considered a complete working solution.



Appendix

Sources

- All photos are from Unsplash.com (https://unsplash.com/license)
- Aggregators <u>https://spark.apache.org/docs/latest/sql-ref-functions-udf-aggregate.html#user-defined-aggregate-functions-udafs</u>
- Aggregators sample notebook: <u>https://docs.databricks.com/_static/notebooks/dataset-aggregator.html</u>
- Window functions <u>https://spark.apache.org/docs/latest/sql-ref-syntax-qry-select-window.html</u>



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Thank you

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