

## Project Phase I

# **Pancreatic Cancer Organoid Profiling – Complete Project Documentation**

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**Title: Pancreatic Cancer Organoid Profiling for Chemotherapy Response Prediction**

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## **Problem Description**

Pancreatic cancer remains one of the deadliest cancers, with limited treatment success and a 5-year survival rate below 12%. Chemotherapy response varies widely between patients, and clinicians currently lack strong predictive markers that determine which treatment would be most effective for a particular individual.

To help solve this, researchers developed *patient-derived organoids* (lab-grown mini-tumors). These organoids mimic the genetics and drug responses of the original tumors and provide an ideal system for studying chemotherapy response.

The dataset we analyzed contains:

- Whole Genome Sequencing
- Whole Exome Sequencing
- RNA-Seq gene expression
- Sample attributes (tumor vs normal, body site, etc.)
- Clinical metadata

Our goal was to transform the raw RNA-Seq gene count data from organoids and create clean, ready-for-analysis data products usable in Power BI, machine learning, or future bioinformatics pipelines.

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## **3. Hypothesis**

Certain gene expression patterns and genetic features in pancreatic cancer organoids correlate with chemotherapy response.

If we profile gene activity accurately, we can identify markers that predict whether a patient will respond to treatment.

This project focuses on preparing the data pipeline that makes such analysis possible.

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## **4. Data Sources**

### **Primary Dataset**

**Pancreatic Cancer Organoid Profiling (dbGaP accession: phs001611.v1.p1)**

- Dataset description:  
[https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study\\_id=phs001611.v1.p1](https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study_id=phs001611.v1.p1)

Open Access RNA-Seq Data (No login needed)

- AWS Open Data Registry:  
<https://registry.opendata.aws/organoid-pancreatic>
- S3 bucket (public):  
`s3://gdc-organoid-pancreatic-phs001611-2-open/`

Gene Reference Annotation (GRCh38 Release 109)

Downloaded from Ensembl:

- [https://ftp.ensembl.org/pub/release-109/gtf/homo\\_sapiens/](https://ftp.ensembl.org/pub/release-109/gtf/homo_sapiens/)

We used:

`Homo_sapiens.GRCh38.109.gtf.gz`

(Not the ab-initio version.)

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## 5. Tools Used

Core Platform

- Databricks for the entire ETL pipeline and validation.

Storage

- Azure Data Lake Storage Gen2 (ADLS) using:
  - SAS Token (Shared Access Signature) authentication

Transformation Framework

- Delta Lake Bronze / Silver / Gold architecture

Visualization

- Power BI Desktop & Power BI Service

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## 6. The Journey: Step-by-Step What We Did

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Step 1 — Configuring ADLS access in Databricks

We configured the connection to Azure Blob Storage using:

- Storage account

- SAS token
- Container
- Mounting / direct ABFSS access

This allowed Databricks to read and write files to:

abfss://project@<storage\_account>.dfs.core.windows.net/

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## Step 2 — Exploring the Raw JSON Matrix

The RNA-Seq gene counts matrix was a wide JSON file, containing:

- 1 column for gene identifiers
- 110+ columns for sample UUIDs
- Many nulls and repeated gene names (non-standard format)

We inspected the schema and discovered:

- Some columns were quality-control artifacts (e.g., N\_multimapping)
- Gene column was incorrectly named "Unnamed: 0"
- Sample names included hyphens and needed normalisation

This was ideal for a Bronze table.

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## 7. Bronze Layer – Raw but Structured Data

Objective:

Store raw data in Delta format, with minimal cleaning.

Actions:

- Renamed "Unnamed: 0" → gene\_id
- Standardised sample column names (replace - with \_)
- Stored the cleaned-but-not-transformed matrix in Delta Lake

Output:

gold/goodreadsreviews60302087/bronze/combined\_counts\_matrix\_raw

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## 8. Silver Layer – Analytical Data (Normalized Shape)

This is where the real transformation happened.

Key Actions:

✓ Unpivoted Wide → Long format

Converted:

gene\_id | sample1 | sample2 | sample3 | ...

→

gene\_id | sample\_uuid | count

✓ Converted nulls to 0 counts

Because most RNA-Seq matrices encode “no reads” as null.

✓ Verified value ranges

We computed:

- minimum count
  - maximum count
- Result: max expression ~896k reads — correct range for raw RNA-Seq.

Stored at:

silver/counts\_long

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## 9. Adding Gene Annotations (Ensembl GTF)

We imported the human reference gene annotation file:

- Parsed all rows where feature = "gene"
- Extracted:
  - gene\_id
  - gene\_name
  - chromosome
  - start/end
  - strand orientation

We then joined this table with the Silver counts table.

Result:

ENSG... identifiers became linked to gene symbols like:

- DDX11L1
- WASH7P
- FAM138A

- PHKA1P1
- TP73-AS2
- etc.

Stored at:  
gold/counts\_with\_genes

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## 10. Gold Layer – Final Curated Datasets (For PowerBI)

**We generated three gold products:**

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### Gene-Level Features

(Gene expression summarised across all samples)

Includes:

- mean log-expression
- standard deviation
- number of samples where gene is expressed
- percent detection

Stored at:  
gold/gene\_features

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### Sample-Level Features

(Characteristics of each organoid sample)

Includes:

- library size (sequencing depth)
- number of detected genes
- % of zero-expressed genes
- mean expression intensity

Stored at:  
gold/sample\_features

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### Normalized Expression Table

(CPM & logCPM values for each gene in each sample)

Used for:

- heatmaps
- clustering
- PCA
- predictive models

Stored at:

gold/normalized\_counts

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## 11. Power BI Integration

What we connected to

In Power BI →

Get Data → Azure → Azure Data Lake Storage Gen2

We selected the Gold folder that contains:

- gene\_features
- sample\_features
- normalized\_counts
- counts\_with\_genes

What we observed

At first, some tables incorrectly showed blank values (backend preview issue), but after loading, the correct numeric columns appeared.

We then created:

- gene-level summary visuals
  - sample quality plots
  - distribution charts
  - zero-inflation heatmaps
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## 12. Challenges Faced

- SAS authentication failures
- Resolved by switching from access keys to SAS token in Spark configs.
- JSON matrix schema irregularities

- Many nulls + weird column names required careful normalization.
  - GTF file mismatch
  - The wrong file (abinitio) caused incorrect annotations.  
Correct version (Homo\_sapiens.GRCh38.109.gtf.gz) fixed it.
  - Large unpivot requiring type casting
  - Because Spark required uniform numeric types.
  - Power BI showing blank preview
  - Resolved when loading the dataset; visualization worked.
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### 13. Conclusion

This project successfully transforms messy, raw RNA-Seq organoid data into clean, structured, fully annotated datasets ready for biomarker discovery.

The resulting Gold tables enable:

- visualization of gene expression patterns
- sample quality control
- identification of genes consistently active
- future machine learning models for predicting chemotherapy response

This is a complete functional foundation for precision oncology analytics.

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### 14. References

- AWS Open Data Registry – Organoid Pancreatic Dataset  
<https://registry.opendata.aws/organoid-pancreatic>
- dbGaP Study phs001611.v1.p1  
[https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study\\_id=phs001611.v1.p1](https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study_id=phs001611.v1.p1)
- Ensembl GRCh38 Release 109 GTF  
[https://ftp.ensembl.org/pub/release-109/gtf/homo\\_sapiens/](https://ftp.ensembl.org/pub/release-109/gtf/homo_sapiens/)