

Implementation Plan - PetroStream Data Pipeline

Goal: Build a Serverless Real-Time Oil & Gas Data Lake on AWS with ML-based Anomaly Detection and Power BI Dashboarding.

Important Note regarding CI/CD:

- **What it manages (Code):** The pipeline logic (Python scripts, Dockerfile, Terraform).
- **What it does NOT manage (Data):** The actual Petrobras Parquet files. CI/CD updates the *machinery* that processes the data, but the data flows through it continuously.

1. Project Architecture

Data Flow

1. **Source:** Local Parquet Files (*/Petrobras Data/*).
 2. **Ingestion (Producer):** Local Python script streams data to AWS Kinesis.
 3. **Processing (ML Consumer):**
 - **Docker Container:** Python application running the ML model.
 - **AWS ECS (Fargate):** Serverless container orchestration.
 - **Application Load Balancer (ALB):** Distributes incoming traffic.
 - **Auto-Scaling:** ECS Service scales up/down based on CPU/Memory usage.
 - **Model: Isolation Forest** (Unsupervised Anomaly Detection).
 - *Training:* Locally on **Mac M4**.
 - *Deployment:* Docker Image pushed to **Amazon ECR**.
 4. **Visualization (Hybrid):**
 - **Custom Web App:** Built with **Streamlit (Python)** for real-time operational views.
 - **BI Tool:** **Power BI** for executive dashboards and historical reporting.
 - **Hosting:** Streamlit on ECS Fargate.
 - **Backend:**
 - Streamlit: Queries Athena via `boto3`.
 - Power BI: Connects to Athena via ODBC Driver.
 - **Features:**
 - Real-time Anomaly Dashboard (Streamlit).
 - Historical Pressure/Temperature Charts (Streamlit + Power BI).
 - Well Status Map.
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2. SQL Usage (Yes, we use SQL!)

We will use **Standard SQL (Presto/Trino dialect)** in **Amazon Athena**.

- **Why?:** S3 stores files (Parquet), but we need to *query* them like a database. Athena allows us to write SQL to scan these files.
 - **What we will do with SQL:**
 1. **Create Tables:** Define the schema of our Parquet files in the Glue Catalog (this can be automatic or manual SQL CREATE EXTERNAL TABLE).
 2. **Analyze Data:**
 - `SELECT * FROM well_data WHERE anomaly_flag = 1;` (Find all anomalies).
 - `SELECT well_id, AVG(pressure) FROM well_data GROUP BY well_id;` (Aggregations).
 3. **Power BI Integration:** Power BI sends SQL queries to Athena behind the scenes to generate your charts.
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3. Local vs. AWS: The Plan

This project is a **Hybrid Workflow**. Here is exactly what runs where:

Local Environment (Your Mac M4)

1. **Data Source:** The Petrobras Parquet files live here.
2. **Model Training:**
 - We write a Python script (`train_model.py`) using `scikit-learn`.
 - We read the Parquet files locally.
 - We train the **Isolation Forest** model on your M4 chip.
 - We save the trained model to a file (`model.joblib`).
3. **Infrastructure as Code (Terraform):**
 - You write `.tf` files locally.
 - You run `terraform apply` locally to tell AWS what to build.
4. **Data Producer:**
 - A Python script (`producer.py`) runs on your Mac.
 - It reads local data and “replays” it to the cloud (AWS Kinesis) as if it were happening live.
5. **Visualization (Power BI):** runs on your Mac, connecting to AWS.

AWS Cloud Environment

1. **Ingestion (Kinesis Data Streams):** Receives the data stream from your Mac.
2. **Compute (AWS Lambda):**
 - Runs the *inference* code (anomaly detection).
 - Downloads the model (`model.joblib`) from S3.

- Scales automatically to handle the data volume.
3. **Storage (S3):**
 - Stores the raw data (Parquet) and the trained model file.
 4. **Catalog (Glue):** Keeps track of the data schema (columns, types).
 5. **Query Engine (Athena):** Executes the SQL queries on the S3 data.
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4. detailed Execution Steps (Documentation)

Phase 1: Infrastructure Setup (Terraform)

1. **Setup:** Configure Terraform provider (`aws`) and backend.
2. **Storage:** Create S3 buckets for `raw-data`, `curated-data`, and `athena-results`.
3. **Streaming:** Create Kinesis Data Stream (`petrostream-ingest`) and Firehose (`petrostream-delivery`).
4. **Security:** Create IAM Roles to allow Kinesis to talk to Firehose, and Firehose to talk to S3.

Phase 2: Machine Learning (Local Training)

1. **Development:** Write `ml/train_model.py`.
2. **Training:** Run the script on Mac to produce `model.joblib`.
3. **Deployment:** Upload `model.joblib` to the S3 bucket created in Phase 1.

Phase 3: Stream Processing (Docker + ECS)

1. **Containerize:** Create a `Dockerfile` for the consumer app.
2. **Registry:** Create an AWS ECR repository and push the Docker image.
3. **Orchestration:**
 - Create an **ECS Cluster** (Fargate).
 - Create a **Task Definition** (CPU/Memory specs).
 - Create an **ECS Service with Auto-Scaling** (e.g., scale out if CPU > 70%).
4. **Networking:**
 - Create an **Application Load Balancer (ALB)**.
 - (Note: For Kinesis processing, ALB is optional as Kinesis “pushes” to consumers, but we can expose an API endpoint on the container to justify the ALB).

Phase 4: Data Producer (Simulation)

1. **Script:** Write `producer/producer.py`.
2. **Logic:** Read local Parquet -> Convert to JSON/Bytes -> `kinesis.put_record()`.
3. **Run:** Start this script in a terminal on your Mac.

4. **Deploy:** Dockerize and deploy to ECS Fargate (same cluster as consumer).
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Phase 5: Frontend Development (Streamlit)

1. **Setup:** Create `dashboard/app.py`.
2. **Components:**
 - *Dashboard:* Summary stats (Total Anomalies, Active Wells).
 - *Charts:* Interactive plots using **Altair** or **Plotly**.
 - *Status:* Live well status indicators.
3. **Integration:** Use `awswrangler` or `boto3` to fetch data from Athena.
4. **Unified Portal:** Add a page or link in Streamlit that opens the Power BI Executive Dashboard.
5. **Deploy:** Dockerize and deploy to ECS Fargate (same cluster as consumer).

Phase 6: Business Intelligence (Power BI)

1. **Setup:** Install AWS Athena ODBC Driver on local machine.
2. **Connection:** Configure Power BI to connect to the Athena Data Source.
3. **Dashboards:**
 - Create “Executive Overview” report.
 - Visualize long-term trends (Monthly/Yearly) that are heavier to compute in real-time.
4. **Publish Report:** (Optional) Share with stakeholders.

Phase 6: CI/CD Pipeline (GitHub Actions)

1. **Workflow:** Create `.github/workflows/deploy.yml`.
2. **Infrastructure:**
 - On push to `main`, run `terraform plan`.
 - (Manual Approval for `terraform apply` to control costs).
3. **Code:**
 - Lint Python code (`flake8`).
 - Build Docker images and push to ECR.
 - Update ECS Service with new image.

Phase 7: Project Teardown & Cost Management (CRITICAL)

1. **Budget Alerts:** Set up AWS Budgets (e.g., alert at \$10).
2. **Destroy:** Run `terraform destroy` to delete all resources (Kinesis, ECS, Lambda, Glue).
3. **S3 Cleanup:** Manually empty S3 buckets (Terraform won't delete non-empty buckets by default).

4. **Result:** \$0 cost when not in use.
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Phase 8: The “Project Switch” (Easy Operations)

To make this easy, we will create a `Makefile` or Shell Scripts to act as your **Single Switch**:

- `./project_up.sh`:
 - Terraform Apply (Infrastructure).
 - Docker Build & Push (Code).
 - Deploy to ECS.
- `./project_down.sh`:
 - Empty S3 Buckets.
 - Terraform Destroy.
 - **Result:** complete shutdown to save money.

Phase 9: Cost Optimization (How we stay under \$120)

1. **Spot Instances:** We will use **Fargate Spot** (Recommended).
 - *Correction:* Spot instances only stop the *compute* (the program running).
 - *Data Safety:* Your data is stored in **S3** and **Kinesis**. It is 100% safe even if the Spot instance stops.
 2. **Retention Policies:**
 - **S3: Keep Data Indefinitely** (Standard Class).
 - **CloudWatch Logs:** Expire logs after 1 day (Metadata only).
 3. **Kinesis Shards:** Use **Provisioned Mode (1 Shard)** or **On-Demand**.
 4. **Lambda:** Tune memory to minimum needed (e.g., 256MB).
 5. **Clean Up:** The `project_down.sh` script is your ultimate safety net.
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5. Dataset Analysis (The Gist)

1. Data Source: Petrobras 3W Dataset

This is the **Petrobras 3W Dataset**, a benchmark for anomaly detection in oil & gas. It contains real (**DRAWN**) and realistic simulated (**SIMULATED**) offshore well data.

2. File Types

- **DRAWN_*.parquet:** Data from **real** offshore wells. These represent actual operational scenarios but are often harder to find in large quantities (hence “rare events”).

- **SIMULATED_*.parquet**: Synthetic data generated to mimic real wells, often used to augment the dataset for training since real anomaly data is scarce.

3. Data Structure (Schema)

From inspecting `SIMULATED_00001.parquet`, the data is **Time-Series Sensor Data** with the following key columns:

- **Timestamp**: Examples show data logged every second (e.g., 2018-10-06 03:57:02).
- **Sensors (The “Features”)**:
 - P-PDG: **Pressure** at the Permanent Downhole Gauge (Bottom-hole pressure).
 - P-TPT: **Pressure** at the Temperature-Pressure Transducer (upstream of the choke).
 - T-TPT: **Temperature** at the Temperature-Pressure Transducer.
 - P-MON-CKP: Pressure upstream of the production choke.
 - T-JUS-CKP: Temperature downstream of the production choke.
 - (And many others like QGL for Gas Lift Flow Rate).
- **Target Variables (The “Labels”)**:
 - **class**: The classification of the event.
 - * 0: **Normal Operation**.
 - * 1, 2, 3...: **Specific Anomalies** (e.g., Abrupt Increase of BSW, Spurious Closure of DHSV, Severe Slugging).
 - **state**: The operational state of the well (e.g., Steady State, Transient).

4. Volume

- **Rows**: The simulated file I checked has ~**59,781 rows** (about 16 hours of data at 1-second intervals).
- **Columns**: 29 columns total (Sensors + Labels + Timestamps).

5. Why This is Perfect for your Project

- **Realism**: You are using industry-standard sensor names (P-PDG, T-TPT).
 - **Pipeline Ready**: The `class` column allows us to instantly verify if our **Lambda Anomaly Detector** is working (we can detect an anomaly and verify if `class != 0`).
 - **Parquet Format**: High-performance format ready for S3/Athena.
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6. User Review Required

- **Ready**: This documented plan is saved.
- **Status**: Waiting for permission to start Phase 1.