







# SageMaker Migration PoC Demo Deck

## Slide 1: Title & Agenda

Element	Content
Title	Accelerating ML with Amazon SageMaker
Subtitle	Proof-of-Concept Demo: Unlocking Scale, Speed, and Efficiency
Goal	Validate technical assumptions and showcase tangible value by addressing key migration objectives.
Agenda	1. Why We're Demoing (Pain Points) 2. Demo 1: Data Preparation ( <b>SageMaker Data Wrangler</b> ) 3. Demo 2: Scalability & Concurrency ( <b>SageMaker Training</b> ) 4. Demo 3: Optimization & Efficiency ( <b>SageMaker Automatic Model Tuning</b> ) 5. Next Steps

# Slide 2: Why We're Demoing: Addressing Your Pain Points

## Reason for Demos (Value-Focused Messaging)

Your Current Challenge	Our SageMaker Solution	Demo Objective
 <b>Slow, Manual Data Prep</b> (Time-consuming feature engineering)	<b>Visual, low-code data transformation</b> and pipeline export.	Validate complex transformation logic.
 <b>Lack of Scalability/GPU Use</b> (Training takes days; no easy GPU access)	<b>Managed, on-demand GPU instances</b> with single-line code changes.	Demonstrate training speedup (CPU vs. GPU).
 <b>Resource Contention</b> (Data scientists waiting for resources)	<b>Isolated, concurrent Training Jobs</b> with automatic resource teardown.	Show multiple jobs running without conflict.
 <b>Manual Optimization</b> (Trial-and-error hyperparameter tuning)	<b>Automated Model Tuning</b> to efficiently find the best performing model.	Confirm objective metric and parameter ranges.

# Slide 3: Demo 1: Data Preparation & Feature Engineering

Service:  Amazon SageMaker Data Wrangler

Section	Explanation	Key Information Gathered
The Problem	Your team spends more time <b>cleaning and preparing data</b> than building models. It's error-prone and hard to reproduce.	<b>Source System Connectivity</b> (e.g., Redshift, Snowflake, S3)
The Solution	Data Wrangler provides a <b>visual interface</b> to inspect data, apply 300+ transformations, and automatically generate the necessary code for pipelines.	<b>Top 3 Transformation Steps</b> your team currently performs manually.
Key Features Shown	1. <b>Data Quality &amp; Insights</b> (Quick analysis of feature distributions). 2. <b>No-Code Transformations</b> (Applying a custom logic, like missing value imputation). 3. <b>Export to Code</b> (Generating a SageMaker Processing Job script).	<b>Desired final Feature Set/Schema.</b>

# Slide 4: Demo 2: Scalability & Concurrency

Service:  Amazon SageMaker Training Jobs







Section	Explanation	Key Information Gathered
The Problem	Your models run on limited CPU capacity. Using GPUs is complex, and <b>concurrent experiments block</b> other data scientists.	<b>Current Model Framework</b> (e.g., PyTorch, TensorFlow) and <b>dependencies</b> .
The Solution	SageMaker manages the compute cluster ( <b>EC2 instances</b> ) for you. You only specify the <b>instance type</b> (CPU or GPU) and the <b>training script</b> .	<b>Current Average Training Time</b> for a specific model.
Key Features Shown	1. <b>Lift-and-Shift Code:</b> Using a simple Python script as the <code>entry_point</code> . 2. <b>GPU Acceleration:</b> Launching the job on an <code>ml.m5.xlarge</code> (CPU) vs. <code>ml.g4dn.xlarge</code> (GPU). 3. <b>Concurrency:</b> Launching <b>multiple, simultaneous training jobs</b> using a single notebook command.	<b>Target Training Time</b> and <b>Maximum Concurrent Users/Jobs</b> needed.

# Slide 5: Demo 3: Optimization & Efficiency

Service:  SageMaker Automatic Model Tuning (AMT)

Section	Explanation	Key Information Gathered
The Problem	Manually searching for the best hyperparameters is a <b>labor-intensive, non-linear process</b> that wastes compute resources and human time.	<b>Key Hyperparameters</b> they manually tune (e.g., learning rate, epochs).
The Solution	AMT uses <b>Bayesian Optimization</b> to intelligently search the parameter space, minimizing cost and time to find the best-performing model configuration.	<b>Objective Metric</b> for model success (e.g., AUC, F1-Score).
Key Features Shown	1. <b>Defining the Search Space</b> ( <code>IntegerParameter</code> , <code>ContinuousParameter</code> ). 2. <b>Setting the Objective</b> (Maximize/Minimize the target metric). 3. <b>Parallel Execution</b> (AMT automatically runs concurrent jobs to speed up the tuning process).	<b>Target Performance Threshold</b> (e.g., "We need an AUC of 0.85").

# Slide 6: Summary & Next Steps

Element	Content
Summary: Value Delivered	 <b>Speed:</b> Move models from days to hours using managed GPU training.  <b>Collaboration:</b> Concurrent jobs enable the whole team to work in parallel.  <b>Intelligence:</b> Automated tuning finds better models, faster, freeing up data scientist time.
Key Client Input Needed	1. Sanitized sample dataset and data access points. 2. A simple version of a current, representative training script ( <code>train_script.py</code> ). 3. Confirmation on target instance types and concurrency needs.
Next Steps	 Finalize technical requirements based on demo feedback.  Develop a detailed Migration Plan (WBS & Timeline).  Move to Phase 1: Pilot Migration.