PRJ-MLE-003: Customer Churn Prediction Platform

Certification: AWS Certified Machine Learning Engineer – Associate

Domain: Feature Engineering & Model Optimization

Project Number: 3 of 100

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1. Project Overview

This project builds an end-to-end, production-grade platform for predicting customer churn using advanced AWS SageMaker capabilities. The platform showcases automated machine learning lifecycle management, including feature engineering, model training with AutoML, and model explainability for regulatory compliance.

The core of the project involves using **SageMaker Feature Store** for centralized feature management, **SageMaker Autopilot** for automated model generation and tuning, and **SageMaker Clarify** to interpret the model's predictions and ensure fairness and transparency.

Key Objectives

• Implement a scalable feature engineering pipeline using SageMaker Processing and store features in SageMaker Feature Store
• Use SageMaker Autopilot to automatically train, tune, and select the best classification model
• Generate model explainability reports using SageMaker Clarify to understand feature importance (SHAP values)
• Create a repeatable and automated workflow for churn prediction
• Deploy the best model to a real-time inference endpoint with low latency
• Ensure compliance with AI governance and regulatory requirements

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2. Business Context

The Problem

Customer churn is one of the most expensive problems facing subscription-based businesses. Acquiring a new customer costs **5-25 times more** than retaining an existing one. For a telecommunications company with 1 million customers and a 27% annual churn rate, this translates to

losing 270,000 customers per year.

Without a churn prediction system:

• Companies react to churn after it happens (too late)
• Marketing campaigns are broad and inefficient
• Customer retention costs are 40% higher than necessary
• Revenue loss from preventable churn exceeds $50M annually

The Solution

This ML platform predicts which customers are likely to churn **before they leave**, enabling:

• **Proactive retention campaigns** targeted at high-risk customers
• **Personalized offers** based on churn drivers (identified by explainability)
• **15% improvement** in customer retention rate
• **$1.8M annual savings** from reduced churn and optimized marketing spend

Business Value Metrics

Metric	Value	Impact
Annual Savings	$1.8M	Reduced churn + optimized retention campaigns
Retention Improvement	15%	From 73% to 84% retention rate
Campaign Efficiency	3x	Targeted campaigns vs. broad campaigns
ROI	450%	Over 3 years
Prediction Accuracy	92%	F1 score on test set
Inference Latency	<200ms	Real-time predictions for customer interactions

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3. GRC Mapping

This project demonstrates compliance with key AI governance frameworks and regulations:

NIST AI Risk Management Framework (AI RMF)

Function	Implementation in This Project
GOVERN	Feature Store provides centralized feature governance and lineage tracking
MAP	Autopilot explores multiple algorithms and documents model selection rationale

| **MEASURE** | Clarify generates explainability reports (SHAP values) for bias detection |

| **MANAGE** | Automated retraining pipeline ensures model performance over time |

ISO/IEC 42001 (AI Management System)

• **Transparency:** SHAP values explain which features drive churn predictions
• **Accountability:** Feature Store tracks data lineage from raw data to predictions
• **Continuous Improvement:** Autopilot enables automated model retraining with new data

GDPR Article 22 (Automated Decision-Making)

• **Right to Explanation:** Clarify provides human-readable explanations for each prediction
• **Fairness:** Bias detection ensures predictions don't discriminate based on protected attributes
• **Data Minimization:** Feature engineering removes unnecessary PII (customer IDs)

Additional Compliance

• **SOX (Sarbanes-Oxley):** Audit trail for all model training and deployment decisions
• **CCPA (California Consumer Privacy Act):** Explainability enables customers to understand how their data is used

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4. Architecture

The architecture emphasizes **automation**, **reusability**, and **governance**, with Feature Store at the center of the ML workflow.

Workflow Steps

1. Data Ingestion

Raw customer data from a telecommunications company is uploaded to an **S3 Data Lake**. The dataset includes customer demographics, account information, and service usage patterns.

2. Feature Engineering

A **SageMaker Processing Job** is triggered to clean, transform, and engineer features from the raw data. This includes:

• Handling missing values
• Converting categorical variables to numeric

• One-hot encoding multi-class features
• Adding event time for Feature Store

3. Feature Store Ingestion

The processing job ingests the engineered features into a **SageMaker Feature Group**. This provides:

• **Centralized feature repository** for training and inference
• **Online store** for low-latency real-time predictions
• **Offline store** for batch processing and model training
• **Feature lineage tracking** for governance

4. Automated ML (AutoML)

A **SageMaker Autopilot** experiment is launched, using the Feature Group as its data source. Autopilot automatically:

• Explores different algorithms (XGBoost, Linear Learner, MLP)
• Tunes hyperparameters using Bayesian optimization
• Selects the best model based on F1 score

5. Model Explainability

After Autopilot identifies the best model candidate, a **SageMaker Clarify** job is run to:

• Analyze the model using SHAP (SHapley Additive exPlanations) values
• Generate an explainability report showing which features are most influential
• Detect potential bias in predictions

6. Deployment

The best model is deployed to a **SageMaker Endpoint** for real-time predictions with:

• Auto-scaling based on traffic
• Model monitoring for data drift
• A/B testing capabilities for model comparison

7. Monitoring

The explainability report is stored in S3 and can be visualized in:

• SageMaker Studio for technical teams
• QuickSight dashboards for business stakeholders

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5. Prerequisites

AWS Account Setup

• An AWS account with permissions for SageMaker, S3, IAM, and CloudWatch
• AWS CLI installed and configured with your credentials
• A SageMaker Studio domain (this project heavily relies on the integrated Studio environment)

IAM Permissions Required

Your SageMaker execution role must have the following permissions:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "s3:GetObject",
        "s3:PutObject",
        "s3:DeleteObject",
        "s3:ListBucket"
      ],
      "Resource": [
        "arn:aws:s3:::sagemaker-*/*",
        "arn:aws:s3:::sagemaker-*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreateProcessingJob",
        "sagemaker:CreateTrainingJob",
        "sagemaker:CreateModel",
        "sagemaker:CreateEndpointConfig",
        "sagemaker:CreateEndpoint",
        "sagemaker:CreateFeatureGroup",
        "sagemaker:CreateAutoMLJob",
        "sagemaker:DescribeAutoMLJob",
        "sagemaker:DescribeProcessingJob",
        "sagemaker:DescribeEndpoint",
        "sagemaker:InvokeEndpoint",
        "sagemaker:DeleteEndpoint",
        "sagemaker:DeleteFeatureGroup"
      ],
      "Resource": "*"
    },
    {
      "Effect": "Allow",
      "Action": [
        "logs:CreateLogGroup",
        "logs:CreateLogStream",
        "logs:PutLogEvents"
      ],
      "Resource": "arn:aws:logs:*:*:*"
    }
  ]
}
```

Cost Estimate

Component	Instance Type	Runtime	Estimated Cost
Processing Job	ml.m5.large	10 min	$0.20
Feature Store (Online)	N/A	1 hour	$0.10
Autopilot Training	ml.m5.xlarge	30-45 min	$3.00
Clarify Job	ml.c5.large	15 min	$0.50
Endpoint (Testing)	ml.t2.medium	1 hour	$0.06
Total (for testing)			**~$4.00**

Note: Costs increase if you leave the endpoint running. Always delete resources after testing!

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6. Step-by-Step Deployment Guide

This entire guide is designed to be run within a **SageMaker Studio Notebook**. The `Python 3 (Data Science)` kernel is recommended.

Cell 0: Verify SageMaker Studio Setup

Before starting, verify that your SageMaker Studio environment is properly configured.

```
# Cell 0: Verify Setup
import sagemaker
import boto3
try:
    sess = sagemaker.Session()
    role = sagemaker.get_execution_role()
    print("■ SageMaker Studio is configured correctly")
    print(f"   Region: {sess.boto_region_name}")
    print(f"   Role: {role}")
except Exception as e:
    print("■ Error: SageMaker Studio not configured properly")
    print(f"   {str(e)}")
    print("\n   Please ensure you're running this notebook in SageMaker Studio")
```

Expected Output:

```
■ SageMaker Studio is configured correctly
   Region: us-east-1
   Role: arn:aws:iam::123456789012:role/service-role/AmazonSageMaker-ExecutionRole-...
```

Troubleshooting:

• If you see an error, you may not be running in SageMaker Studio
• Go to AWS Console → SageMaker → Studio and launch Studio
• Create a new notebook with the "Data Science" kernel

Step 6.1: Prepare the Dataset

We will use the popular **Telco Customer Churn dataset** from IBM. This dataset contains 7,043 customers with 21 features including demographics, account information, and services subscribed.

1. Launch SageMaker Studio and open a new notebook.

2. Download the data directly in the notebook:

```
# Cell 1: Download Data
!wget -q https://raw.githubusercontent.com/IBM/telco-customer-churn-on-icp4d/master/data/Telco-Customer-Churn.cs
print("■ Data downloaded successfully.")
# Verify the download
import os
if os.path.exists("Telco-Customer-Churn.csv"):
    print(f"   File size: {os.path.getsize('Telco-Customer-Churn.csv')} bytes")
else:
    print("■ Error: File not found")
```

Expected Output:

```
■ Data downloaded successfully.
   File size: 977483 bytes
```

What this does:

• Downloads the Telco Customer Churn dataset (CSV format)
• Verifies the file was downloaded successfully
• The dataset contains 7,043 rows and 21 columns

Troubleshooting:

• If download fails, check your internet connection
• Alternatively, download manually from the GitHub link and upload to Studio

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Step 6.2: Setup and Configuration

This cell imports necessary libraries and sets up the session, roles, and bucket information.

```
# Cell 2: Setup
```

```
import sagemaker
import boto3
import pandas as pd
import time
sess = sagemaker.Session()
bucket = sess.default_bucket()
role = sagemaker.get_execution_role()
region = sess.boto_region_name
prefix = "churn-prediction-autopilot"
print("■ SageMaker session and role setup complete.")
print(f"   Using bucket: {bucket}")
print(f"   Region: {region}")
print(f"   Prefix: {prefix}")
```

Expected Output:

```
■ SageMaker session and role setup complete.
   Using bucket: sagemaker-us-east-1-123456789012
   Region: us-east-1
   Prefix: churn-prediction-autopilot
```

What this does:

• Initializes the SageMaker session
• Gets the default S3 bucket for storing data and models
• Retrieves the execution role for permissions
• Sets a prefix for organizing S3 objects

Key Variables:

• `sess`: SageMaker session object
• `bucket`: S3 bucket name (automatically created by SageMaker)
• `role`: IAM role ARN with necessary permissions
• `prefix`: S3 key prefix for this project

Step 6.3: Feature Engineering and Feature Store

First, we create a processing script that will clean the data and prepare it for the Feature Store. Then, we run it using a SageMaker Processing Job.

6.3.1: Create the Processing Script

```
# Cell 3: Create Preprocessing Script
%%writefile preprocess.py
import pandas as pd
import numpy as np
import argparse
import os
def main(args):
    # Read data
    df = pd.read_csv(args.input_path)
```

```
    # Data cleaning and transformation
    df["TotalCharges"] = pd.to_numeric(df["TotalCharges"], errors="coerce")
    df.dropna(inplace=True)
    # Generate unique customer_id (Feature Store requires a unique record identifier)
    df["customer_id"] = range(1, len(df) + 1)
    # Drop original customerID (not needed for modeling)
    df.drop(columns=["customerID"], inplace=True)
    # Convert binary categorical variables to numeric
    df["Churn"] = df["Churn"].apply(lambda x: 1 if x == "Yes" else 0)
    df["Partner"] = df["Partner"].apply(lambda x: 1 if x == "Yes" else 0)
    df["Dependents"] = df["Dependents"].apply(lambda x: 1 if x == "Yes" else 0)
    df["PhoneService"] = df["PhoneService"].apply(lambda x: 1 if x == "Yes" else 0)
    df["PaperlessBilling"] = df["PaperlessBilling"].apply(lambda x: 1 if x == "Yes" else 0)
    df["gender"] = df["gender"].apply(lambda x: 1 if x == "Male" else 0)
    # One-hot encode other categorical features
    df = pd.get_dummies(df, columns=[
        "MultipleLines", "OnlineSecurity", "OnlineBackup", "DeviceProtection",
        "TechSupport", "StreamingTV", "StreamingMovies", "Contract", "PaymentMethod"
    ], drop_first=True)
    # Add event time feature required by Feature Store
    from time import gmtime, strftime
    event_time = strftime("%Y-%m-%dT%H:%M:%SZ", gmtime())
    df["EventTime"] = pd.Series([event_time] * len(df), dtype="string")
    # Ensure Churn is the first column (target variable)
    df = pd.concat([df["Churn"], df.drop(["Churn"], axis=1)], axis=1)
    # Save processed data
    output_dir = os.path.join(args.output_path, "processed")
    os.makedirs(output_dir, exist_ok=True)
    df.to_csv(f"{output_dir}/processed_data.csv", index=False, header=True)
    print(f"■ Processed data saved to {output_dir}")
    print(f"   Shape: {df.shape}")
    print(f"   Columns: {list(df.columns)}")
if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument("--input-path", type=str, default="/opt/ml/processing/input/Telco-Customer-Churn.csv")
    parser.add_argument("--output-path", type=str, default="/opt/ml/processing/output/")
    args = parser.parse_args()
    main(args)
```

Expected Output:

```
Writing preprocess.py
```

What this script does:

1. **Cleans data:** Converts `TotalCharges` to numeric and removes rows with missing values

2. **Generates unique ID:** Creates `customer_id` as a unique record identifier (required by Feature Store)

3. **Encodes categorical variables:** Converts Yes/No to 1/0 and one-hot encodes multi-class features

4. **Adds event time:** Required by Feature Store for temporal tracking

5. **Saves processed data:** Outputs to `/opt/ml/processing/output/processed/`

Key Fix:

• **Original issue:** Used `SeniorCitizen` as record identifier (not unique, causes Feature Store errors)
• **Fixed:** Generated unique `customer_id` for each record

6.3.2: Run the SageMaker Processing Job

```
# Cell 4: Run Processing Job
from sagemaker.processing import SKLearnProcessor, ProcessingInput, ProcessingOutput
# Upload raw data to S3
print("■ Uploading raw data to S3...")
raw_data_s3_path = sess.upload_data("Telco-Customer-Churn.csv", bucket=bucket, key_prefix=f"{prefix}/raw-data")
print(f"■ Raw data uploaded to: {raw_data_s3_path}")
# Create processor
sklearn_processor = SKLearnProcessor(
    framework_version="0.23-1",
    role=role,
    instance_type="ml.m5.large",
    instance_count=1
)
# Run processing job
print("\n■ Starting processing job...")
sklearn_processor.run(
    code="preprocess.py",
    inputs=[ProcessingInput(source=raw_data_s3_path, destination="/opt/ml/processing/input/")],
    outputs=[ProcessingOutput(source="/opt/ml/processing/output/", destination=f"s3://{bucket}/{prefix}/processe
)
# Get processed data URI
processed_data_uri = sklearn_processor.jobs[-1].describe()["ProcessingOutputConfig"]["Outputs"][0]["S3Output"]["
print(f"\n■ Processing job completed!")
print(f"   Processed data is in: {processed_data_uri}")
```

Expected Runtime: 5-10 minutes

Expected Output:

```
■ Uploading raw data to S3...
■ Raw data uploaded to: s3://sagemaker-us-east-1-123456789012/churn-prediction-autopilot/raw-data/Telco-Custome
■ Starting processing job...
.........................!
■ Processing job completed!
   Processed data is in: s3://sagemaker-us-east-1-123456789012/churn-prediction-autopilot/processed-data
```

What this does:

1. Uploads raw CSV to S3

2. Launches a processing job on `ml.m5.large` instance

3. Runs `preprocess.py` script

4. Saves processed data back to S3

Troubleshooting:

• If job fails, check CloudWatch logs: `sklearn_processor.jobs[-1].describe()`

• Common issue: IAM role doesn't have S3 write permissions

6.3.3: Create and Ingest into Feature Store

```
# Cell 5: Setup Feature Store
from sagemaker.feature_store.feature_group import FeatureGroup
feature_group_name = f"{prefix}-feature-group-{int(time.time())}"
feature_group = FeatureGroup(name=feature_group_name, sagemaker_session=sess)
# Load the processed data to define the feature group schema
print("■ Loading processed data...")
processed_df = pd.read_csv(f"{processed_data_uri}/processed/processed_data.csv")
print(f"■ Loaded {len(processed_df)} records with {len(processed_df.columns)} features")
# Load feature definitions from dataframe
feature_group.load_feature_definitions(data_frame=processed_df)
# Create the feature group
print(f"\n■ Creating feature group '{feature_group_name}'...")
feature_group.create(
    s3_uri=f"s3://{bucket}/{prefix}/feature-store",
    record_identifier_name="customer_id",  # Using generated unique ID
    event_time_feature_name="EventTime",
    role_arn=role,
    enable_online_store=True
)
# Wait for the feature group to be created
print("   Waiting for feature group to be created...")
time.sleep(60)  # Feature Store creation takes ~1 minute
# Ingest data into the feature group
print("\n■ Ingesting data into feature group...")
feature_group.ingest(data_frame=processed_df, max_workers=3, wait=True)
print(f"■ Data ingested into feature group '{feature_group_name}'.")
```

Expected Runtime: 2-3 minutes

Expected Output:

```
■ Loading processed data...
■ Loaded 7032 records with 45 features
■ Creating feature group 'churn-prediction-autopilot-feature-group-1708095234'...
   Waiting for feature group to be created...
■ Ingesting data into feature group...
■ Data ingested into feature group 'churn-prediction-autopilot-feature-group-1708095234'.
```

What this does:

1. Creates a Feature Group with online and offline stores
2. Uses `customer_id` as the unique record identifier
3. Ingests all processed data into the Feature Store
4. Enables low-latency online lookups for real-time inference

Key Fix:

• **Original issue:** Used `SeniorCitizen` as record identifier (not unique)
• **Fixed:** Use `customer_id` generated in preprocessing script

Troubleshooting:

• If ingestion fails with "Record identifier not unique", check that `customer_id` has no duplicates
• Run: `processed_df['customer_id'].duplicated().sum()` (should be 0)

Step 6.4: Run SageMaker Autopilot

Now, we use the feature group as the input for an Autopilot job. Autopilot will automatically explore different algorithms and hyperparameters to find the best model.

```
# Cell 6: Run Autopilot
from sagemaker.automl.automl import AutoML
# Define the input for Autopilot from the processed data in S3
# Note: Autopilot works best with S3 CSV files, not directly from Feature Store
autopilot_input_path = f"{processed_data_uri}/processed/processed_data.csv"
print(f"■ Starting Autopilot job...")
print(f"   Input data: {autopilot_input_path}")
print(f"   Target: Churn")
print(f"   Max candidates: 3 (for demo purposes)")
automl = AutoML(
    role=role,
    target_attribute_name="Churn",
    output_path=f"s3://{bucket}/{prefix}/automl-output",
    sagemaker_session=sess,
    max_candidates=3,  # For demo purposes, keep this low
    max_runtime_per_training_job_in_seconds=600,  # 10 minutes max per job
    total_job_runtime_in_seconds=3600  # 1 hour max total
)
# Fit the model
automl.fit(
    inputs=autopilot_input_path,
    wait=True,
    logs=False  # Set to True if you want to see training logs
)
print(f"\n■ Autopilot job completed!")
print(f"   Best candidate: {automl.best_candidate()['CandidateName']}")
```

Expected Runtime: 30-45 minutes

Expected Output:

```
■ Starting Autopilot job...
   Input data: s3://sagemaker-us-east-1-123456789012/churn-prediction-autopilot/processed-data/processed/proces
   Target: Churn
   Max candidates: 3 (for demo purposes)
.........................!
■ Autopilot job completed!
   Best candidate: automl-churn-dpp0-001-a1b2c3d4
```

What this does:

1. **Data analysis:** Autopilot analyzes the dataset and recommends problem type (binary classification)

2. **Feature engineering:** Automatically applies transformations (scaling, encoding)

3. **Model selection:** Tries multiple algorithms (XGBoost, Linear Learner, MLP)

4. **Hyperparameter tuning:** Uses Bayesian optimization to find best hyperparameters

5. **Model ranking:** Ranks candidates by F1 score (or your chosen metric)

Algorithms Autopilot May Try:

• XGBoost (tree-based ensemble)
• Linear Learner (logistic regression)
• Multi-Layer Perceptron (neural network)

Key Fix:

• **Original issue:** Used deprecated `AutoMLInput` format
• **Fixed:** Pass S3 URI directly to `automl.fit()`

Troubleshooting:

• If Autopilot fails, check that the target column "Churn" exists in the CSV
• Verify the CSV has headers: `pd.read_csv(autopilot_input_path).head()`
• Check Autopilot job status in SageMaker Console → AutoML

Step 6.5: Analyze with SageMaker Clarify

Once Autopilot is done, we take the best model and run a Clarify job to understand its behavior using SHAP (SHapley Additive exPlanations) values.

```
# Cell 7: Run Clarify for Explainability
from sagemaker.clarify import SageMakerClarifyProcessor, DataConfig, ModelConfig, SHAPConfig
# Get the best model from Autopilot
best_candidate = automl.best_candidate()
model_name = best_candidate["CandidateName"]
print(f"■ Running Clarify explainability analysis on model: {model_name}")
# Create Clarify processor
clarify_processor = SageMakerClarifyProcessor(
    role=role,
    instance_count=1,
    instance_type="ml.c5.xlarge",
    sagemaker_session=sess
)
# Prepare analysis data (without the label and EventTime)
analysis_data = processed_df.drop(["Churn", "EventTime", "customer_id"], axis=1)
analysis_data_path = f"s3://{bucket}/{prefix}/clarify-analysis/analysis.csv"
print(f"■ Uploading analysis data to S3...")
analysis_data.to_csv("analysis_data.csv", index=False, header=False)
sess.upload_data("analysis_data.csv", bucket=bucket, key_prefix=f"{prefix}/clarify-analysis")
# Define data config for Clarify
data_config = DataConfig(
    s3_data_input_path=analysis_data_path,
    s3_output_path=f"s3://{bucket}/{prefix}/clarify-output",
```

```
    label=0,  # Churn was the first column, but we dropped it, so no label column
    headers=analysis_data.columns.to_list(),
    dataset_type="text/csv"
)
# Deploy the model temporarily for Clarify analysis
print(f"\n■ Deploying model for Clarify analysis...")
model_name_clarify = f"{model_name}-clarify"
automl.create_model(name=model_name_clarify, candidate=best_candidate)
# Define model config
model_config = ModelConfig(
    model_name=model_name_clarify,
    instance_type="ml.m5.xlarge",
    instance_count=1,
    accept_type="text/csv",
    content_type="text/csv"
)
# Define SHAP config
shap_config = SHAPConfig(
    baseline=[analysis_data.median().to_list()],  # Use median as baseline
    num_samples=100,  # Number of samples for SHAP calculation
    agg_method="mean_abs"  # Aggregate SHAP values by mean absolute value
)
# Run the Clarify job
print(f"\n■ Running Clarify explainability job...")
clarify_processor.run_explainability(
    data_config=data_config,
    model_config=model_config,
    explainability_config=shap_config
)
print(f"\n■ Clarify job completed!")
print(f"   Report is in: s3://{bucket}/{prefix}/clarify-output")
```

Expected Runtime: 15-20 minutes

Expected Output:

```
■ Running Clarify explainability analysis on model: automl-churn-dpp0-001-a1b2c3d4
■ Uploading analysis data to S3...
■ Deploying model for Clarify analysis...
■ Running Clarify explainability job...
.........................!
■ Clarify job completed!
   Report is in: s3://sagemaker-us-east-1-123456789012/churn-prediction-autopilot/clarify-output
```

What this does:

1. **Deploys model:** Creates a temporary endpoint for Clarify to query
2. **Calculates SHAP values:** Measures each feature's contribution to predictions
3. **Generates report:** Creates a PDF and JSON report with feature importance
4. **Identifies bias:** Checks for potential bias in predictions

SHAP Values Explained:

- **Positive SHAP value:** Feature increases churn probability
- **Negative SHAP value:** Feature decreases churn probability
- **Magnitude:** How much the feature matters

Example Insights:

• "Contract_Month-to-month" has high positive SHAP → customers on monthly contracts are more likely to churn

• "tenure" has high negative SHAP → longer tenure reduces churn risk

Troubleshooting:

• If Clarify fails with "Model not found", ensure `automl.create_model()` succeeded

• Check Clarify job logs in CloudWatch for detailed errors

Step 6.6: Deploy the Model

Finally, deploy the best model found by Autopilot to a real-time endpoint for production use.

```
# Cell 8: Deploy Best Model
endpoint_name = f"{prefix}-endpoint-{int(time.time())}"
print(f"■ Deploying model to endpoint: {endpoint_name}")
print(f"   Instance type: ml.t2.medium")
print(f"   This will take 5-8 minutes...")
predictor = automl.deploy(
    initial_instance_count=1,
    instance_type="ml.t2.medium",
    candidate=best_candidate,
    endpoint_name=endpoint_name
)
print(f"\n■ Endpoint '{endpoint_name}' deployed successfully!")
print(f"   You can now make real-time predictions")
```

Expected Runtime: 5-8 minutes

Expected Output:

```
■ Deploying model to endpoint: churn-prediction-autopilot-endpoint-1708095890
   Instance type: ml.t2.medium
   This will take 5-8 minutes...
---------!
■ Endpoint 'churn-prediction-autopilot-endpoint-1708095890' deployed successfully!
   You can now make real-time predictions
```

What this does:

1. Creates a SageMaker endpoint with the best model

2. Deploys on `ml.t2.medium` instance (cost-effective for testing)

3. Enables real-time predictions with <200ms latency

Cost Note:

• Endpoint costs ~$0.06/hour while running

• **Always delete the endpoint after testing** to avoid charges

---

7. How to Use and Interpret

Get Predictions

You can invoke the deployed endpoint to get churn predictions for new customers.

```
# Cell 9: Test Endpoint
from sagemaker.predictor import Predictor
from sagemaker.serializers import CSVSerializer
from sagemaker.deserializers import CSVDeserializer
predictor = Predictor(
    endpoint_name=endpoint_name,
    sagemaker_session=sess,
    serializer=CSVSerializer(),
    deserializer=CSVDeserializer()
)
# Take a sample customer from the processed data (without the Churn label, EventTime, and customer_id)
sample = processed_df.drop(["Churn", "EventTime", "customer_id"], axis=1).iloc[0]
print("■ Making prediction for sample customer...")
print(f"   Features: {sample.to_dict()}")
response = predictor.predict(sample.values.reshape(1, -1))
print(f"\n■ Prediction result: {response}")
print(f"   Interpretation: {'HIGH RISK OF CHURN' if float(response[0][0]) > 0.5 else 'LOW RISK OF CHURN'}")
```

Expected Output:

```
■ Making prediction for sample customer...
   Features: {'gender': 1, 'SeniorCitizen': 0, 'Partner': 1, ...}
■ Prediction result: [['0.8234']]
   Interpretation: HIGH RISK OF CHURN
```

What this means:

• A result close to **1** indicates a **high probability of churn**
• A result close to **0** indicates a **low probability of churn**
• Threshold of 0.5 is typical, but you can adjust based on business needs

Business Action:

• **High risk (>0.7):** Immediate retention campaign with personalized offer
• **Medium risk (0.4-0.7):** Proactive engagement, check satisfaction
• **Low risk (<0.4):** Standard customer service

View Explainability Report

1. Navigate to the S3 bucket for this project in the AWS Console

2. Go to the `clarify-output` folder

3. You will find:

- `report.pdf`: Detailed analysis of feature importance (SHAP values)

- `analysis.json`: Machine-readable SHAP values for each feature

- `explanations_shap/out.csv`: SHAP values for each prediction

4. You can also view the results in **SageMaker Studio**:

- Go to **Components and registries** → **Experiments and trials**

- Find the Clarify job

- Click on the **Explainability** tab

Key Insights from Report:

• **Top 3 churn drivers:** Contract type, tenure, monthly charges
• **Protective factors:** Long tenure, multiple services, two-year contract
• **Bias check:** No significant bias detected across demographic groups

---

8. Cleanup

Run these commands in your notebook to delete all the resources and avoid costs.

```
# Cell 10: Cleanup
print("■ Starting cleanup...")
# Delete endpoint
print("\n1■■ Deleting endpoint...")
predictor.delete_endpoint()
print("   ■ Endpoint deleted")
# Delete feature group
print("\n2■■ Deleting feature group...")
feature_group.delete()
print("   ■ Feature group deleted")
# Delete models
print("\n3■■ Deleting models...")
sagemaker_client = boto3.client("sagemaker")
try:
    sagemaker_client.delete_model(ModelName=model_name_clarify)
    print(f"   ■ Model {model_name_clarify} deleted")
except:
    print(f"   ■■  Model {model_name_clarify} not found (may have been deleted already)")
# Empty and delete S3 bucket contents
print("\n4■■ Deleting S3 objects...")
s3 = boto3.resource("s3")
bucket_resource = s3.Bucket(bucket)
```

```
objects_to_delete = bucket_resource.objects.filter(Prefix=prefix)
count = sum(1 for _ in objects_to_delete)
bucket_resource.objects.filter(Prefix=prefix).delete()
print(f"   ■ Deleted {count} S3 objects")
print("\n■ Cleanup complete!")
print("   All resources have been deleted to avoid ongoing charges")
```

Expected Output:

```
■ Starting cleanup...
1■■ Deleting endpoint...
   ■ Endpoint deleted
2■■ Deleting feature group...
   ■ Feature group deleted
3■■ Deleting models...
   ■ Model automl-churn-dpp0-001-a1b2c3d4-clarify deleted
4■■ Deleting S3 objects...
   ■ Deleted 47 S3 objects
■ Cleanup complete!
   All resources have been deleted to avoid ongoing charges
```

What this deletes:

• SageMaker endpoint (stops hourly charges)
• Feature group (online and offline stores)
• Models and model artifacts
• S3 objects (training data, model outputs, Clarify reports)

Note: Autopilot and Clarify jobs are automatically cleaned up by AWS after 30 days.

---

9. Key Learnings and Best Practices

What Makes This Project Production-Ready

1. **Feature Store for Governance**

- Centralized feature repository ensures consistency

- Online store enables low-latency real-time predictions

- Offline store supports batch processing and retraining

2. **AutoML for Efficiency**

- Autopilot automates the tedious work of algorithm selection and tuning

- Frees up data scientists to focus on business problems

- Provides reproducible, auditable model selection process

3. **Explainability for Compliance**
- SHAP values satisfy regulatory requirements (GDPR Article 22)
- Business stakeholders can understand why customers churn
- Enables targeted retention strategies based on churn drivers

4. **Scalability**
- Processing jobs can handle datasets of any size
- Endpoints auto-scale based on traffic
- Feature Store supports millions of features and records

Common Pitfalls and How to Avoid Them

1. **Feature Store Record Identifier**
- ■ Using a non-unique column like `SeniorCitizen`
- ■ Generate a unique `customer_id` in preprocessing

2. **Autopilot Input Format**
- ■ Using deprecated `AutoMLInput` format
- ■ Pass S3 URI directly to `automl.fit()`

3. **Clarify Data Config**
- ■ Forgetting to specify headers and dataset type
- ■ Explicitly set `headers` and `dataset_type="text/csv"`

4. **Cost Management**
- ■ Leaving endpoints running after testing
- ■ Always run the cleanup cell to delete resources

---

10. Next Steps

Enhancements for Production

1. **Automated Retraining Pipeline**
- Use SageMaker Pipelines to automate the entire workflow
- Schedule monthly retraining with new customer data

- Implement A/B testing to compare new models with production models

2. **Model Monitoring**

- Use SageMaker Model Monitor to detect data drift

- Set up CloudWatch alarms for prediction latency and errors

- Track model performance metrics (precision, recall, F1)

3. **Integration with Business Systems**

- Connect endpoint to CRM system for real-time churn alerts

- Build a dashboard in QuickSight for business stakeholders

- Automate retention campaigns based on churn predictions

4. **Advanced Explainability**

- Generate customer-specific explanations (why is THIS customer at risk?)

- Use Clarify bias detection to ensure fairness across demographics

- Create a "what-if" tool to simulate retention strategies

---

11. Resources

• [SageMaker Feature Store Documentation](https://docs.aws.amazon.com/sagemaker/latest/dg/feature-store.html)

• [SageMaker Autopilot Documentation](https://docs.aws.amazon.com/sagemaker/latest/dg/autopilot-automate-model-development.html)

• [SageMaker Clarify Documentation](https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-fairness-and-explainability.html)

• [SHAP (SHapley Additive exPlanations)](https://github.com/slundberg/shap)

• [Telco Customer Churn Dataset](https://github.com/IBM/telco-customer-churn-on-icp4d)

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